Final Report

STATEWIDE PRICING PILOT
SUMMER 2003 IMPACT ANALYSIS

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Table of Contents

Table of Contents

1. Executive Summary

This is the final report containing impact estimates, demand models, and elasticities of demand for the Statewide Pricing Pilot (SPP) for the summer of 2003. It replaces earlier reports that were issued in January and March. A final report containing results from the summers of 2003 and 2004 and the winter of 2003-04 will be issued in the first quarter of 2005.

The SPP involves roughly 2,000 residential and small commercial and industrial (C&I) customers[1] located in the service territories of Pacific Gas & Electric Company, San Diego Gas & Electric Company and Southern California Edison. Most customers enrolled in the pricing pilot were either placed on experimental, time-of-use (TOU) or dynamic pricing tariffs or given dynamic pricing information to encourage demand response. Other customers were selected as a control group and were kept on their existing tariffs and monitored at the same time.

The tariffs being tested in the SPP include a time-of-use (TOU) rate and two types of critical peak pricing (CPP) rates. The TOU rate offers customers an on-peak price that is higher than the average price for the standard rate, and an off-peak price that is lower than the average price. The two CPP rates (CPP-F and CPP-V) include a substantially higher on-peak price (50 to 75 cents/kWh) for 15 "critical" days of the year and a standard TOU on-peak price on all other days. CPP-F features the same fixed, on-peak period on both critical and non-critical days with day-ahead customer notification, while CPP-V features a variable-length on-peak period on critical days, and customers may be notified on the day of the critical peak event.[2]

The specific prices by time period for each rate vary across utilities and climate zones, as they are layered on top of the existing five-tier rate structure, which varies by utility and climate zone (due to differences in baseline quantities by climate zone). Figure 1-1 shows an example of the average price by rate period for a Tier-3, residential customer in climate zone 2 in PG&E's service territory for the CPP-F and TOU experimental tariffs. It also shows the average price for control group customers who face the standard, five-tier rate that is in effect for the majority of consumers who are not in the experiment.

Figure 1-2 illustrates the residential CPP-V tariff, which was tested only in the SDG&E service territory. As seen, each treatment has two sets of rates that differ with respect to the prices charged in each rate period. While these rates are close to revenue neutral

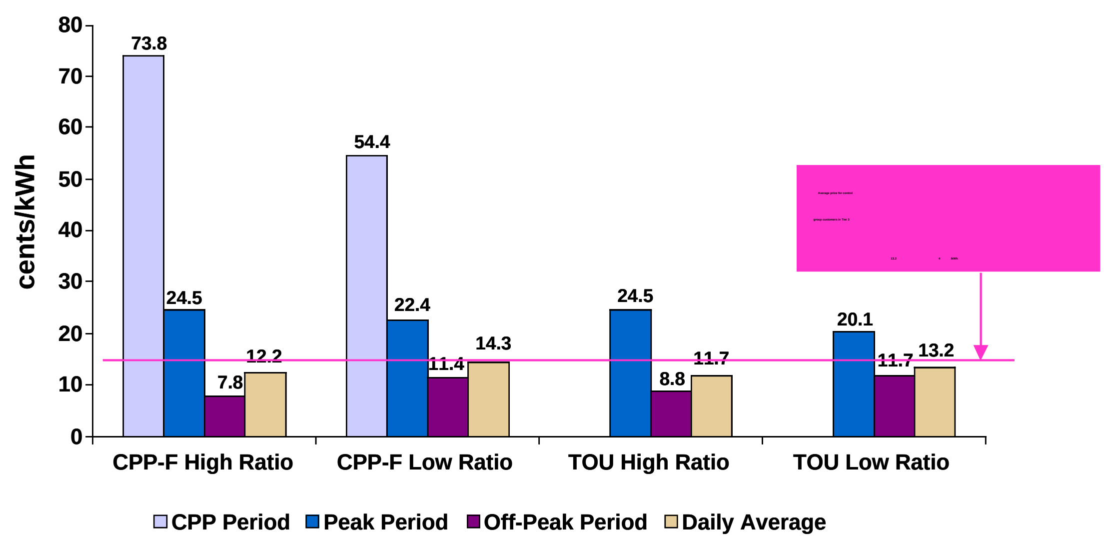
[1] Small C&I customers are divided into two segments, those with billing demand less than 20 kW and those with billing demand between 20 kW and 200 kW.

[2] The peak period for all residential tariffs is from 2 pm to 7 pm on weekdays. The critical peak period for the CPP-F rate is also from 2 pm to 7 pm on CPP-event days. The critical peak period for the CPP-V tariff varies between 2 hours and 5 hours during the period from 2 pm to 7 pm on CPP-event days.

on an annual basis, they are not seasonally revenue neutral, as seasonally revenue neutral rates would not allow for estimation of all own- and cross-price elasticities.[3]

Although the “high ratio” rates have higher ratios between critical-peak and off-peak prices and between peak and off-peak prices than do the “low ratio” tariffs, the average

Figure 1-1
Average For Customer At Midpoint of Tier 3
(PG&E Summer Period, Climate Zone 2)



daily price is actually lower for the “high ratio” tariff than for the “low ratio” tariff.[4]

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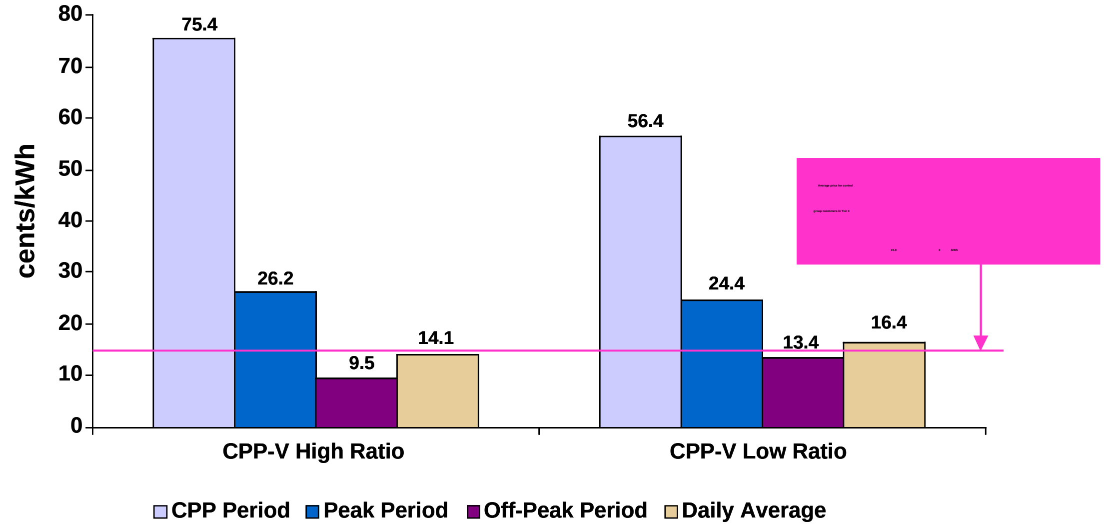
3 The own price elasticity of demand equals the percent change in the quantity of electricity consumed in a specific time period (e.g., the peak period) divided by the percent change in the price of electricity in that period. The cross-price elasticity equals the percent change in the quantity of electricity used in a period divided by the percent change in the price of electricity in another period.

4 The various constraints and objectives associated with the experimental rate design are summarized in section 3.2.5.

Figure 1-2
Average Experimental Price For Customer At Midpoint of Tier 3
(SDG&E Summer Period, Zone 2)



All three of the SPP experimental rates were tested for residential customers whereas only TOU and CPP-V rates were tested for small C&I customers. All small C&I customers are located in the SCE service area.[5]

Customers in the SPP were divided into four climate zones across the three utilities to assess whether responsiveness varies across geographic/climatic regions. Customers enrolled in the different rates as well as control customers were also divided into three sample design "tracks" (A, B and C). Track A was designed to be representative of the general population in the state. Track B is geographically-specific to residential customers located in the areas around San Francisco near operating power plants. Track C consists of residential and C&I customers who were already participating in a demand response pilot in Southern California (Smart Thermostat program implemented under Assembly Bill 970). Only results from Tracks A and C are provided in this report. A separate report covering the Track B analysis will be produced before the end of the year.

The impact evaluation summarized in this report has two primary objectives. The most important objective is the development of electricity demand models that can be used to

[5] An additional "Information Only" non-rate treatment was also tested for residential customers in the PG&E service area. This treatment involved notifying customers of CPP event days and asking them to reduce energy use during the peak period. These customers were not placed on any of the SPP tariffs (i.e., their prices did not change). Analysis for this treatment is not yet complete and, therefore, is not included in this report.

predict the impact of a variety of time-varying prices on energy use by time period, including prices that were not specifically tested in the SPP. The second objective is to produce estimates of the impact of the specific rates tested in the SPP. It is important to note that the impact estimates for the specific tariffs tested in the SPP should not be used for policy analysis for several reasons:

- As indicated above, the SPP rates are not seasonally revenue neutral and have lower average prices when the peak to off-peak price ratio is high and higher average prices when it is low. These rates were designed primarily to develop price elasticity estimates and were also subject to a number of design constraints required by the California Public Utilities Commission (CPUC). As such, they may not be the rates that would likely be implemented in a non-experimental setting.

- The impact estimates represent the average impact across both the high and low ratio tariffs, not what would be found for any single tariff.

- The estimates represent the average weather in the treatment period for Summer 2003. They have not been adjusted to represent "typical" or long-term average weather conditions.

Two types of demand model specifications were estimated in this study. One specification, called the Constant Elasticity of Substitution (CES) model, consists of two equations. One of the CES equations estimates the relationship between the ratio of energy used in one period (e.g., the peak period) relative to energy used in the other period (e.g., the off-peak period) and the ratio of prices in the two periods. A summary measure of this relationship is called the elasticity of substitution, which defines the change in the share of peak period energy use to off-peak energy use. The second CES equation examines the change in daily energy use as a result of the change in daily prices. A summary measure of this relationship is the daily price elasticity of demand. The combination of the elasticity of substitution and the daily price elasticity can be used to predict the impact of a change in prices on both peak and off-peak period energy use. The larger the absolute value of the elasticity of substitution, the more responsive customers are to price changes, everything else held equal. However, whether energy use in the peak or off-peak periods goes up or down is determined by the combination of the elasticity of substitution and the daily price elasticity.

The second demand model specification, called the double-log (DL), involves estimating separate equations for peak and off-peak period energy use. Energy use in each period is a function of the price in that period as well as the price in the other period.[6] A summary measure of price responsiveness is the price elasticity of demand for energy. The own price elasticity of demand equals the percent change in the quantity of electricity consumed in a specific time period (e.g., the peak period) divided by the percent change in the price of electricity in that period. The larger the own-price

[6] Other terms are also included in each regression, as explained in sections 4 through 6 of this report.

elasticity of demand, the more responsive customers are to price changes, everything else being equal. The cross-price elasticity equals the percent change in the quantity of electricity used in a period divided by the percent change in the price of electricity in another period. Thus, the change in energy use in a specific rate period is a function of both the change in price in that rate period as well as the change in price in the other rate period.

1.1 KEY FINDINGS FOR RESIDENTIAL CUSTOMERS

Demand models were initially estimated separately for each climate zone for the CPP-F rate treatment. In the majority of regressions, price was found to be statistically significant and price elasticities and elasticities of substitution were found to be comparable to those in the literature. Demand responsiveness was found to be greater in the hotter climate zones (zones 3 and 4) than in the cooler zones (zones 1 and 2).

Ultimately, the data was pooled across climate zones and the model specification was modified to include interaction terms between weather and price and a variable representing central air conditioning ownership and price. These interaction terms allow price responsiveness to vary with weather and air conditioning ownership. Once these two factors are accounted for, no statistically significant differences were found across climate zones. That is, price responsiveness varies across climate zones because of differences in weather and air conditioning ownership. The differences in price elasticities and impacts reported below are based on the pooled database with weather/price and air conditioning/price interaction terms included in the specification.

Table 1-1 presents summary measures of price response from the CES specification based on analysis of the CPP-F treatment and Table 1-2 presents the price elasticities obtained from the double-log model specification. The average elasticity of substitution is -0.069 and the average price elasticity of daily energy use on weekdays is –0.023. The elasticity of substitution increases significantly across climate zones, from a low of -0.032 in zone 1 to a high of -0.111 in zone 4. The weekday, daily price elasticity is much more constant across the climate zones.

Table 1-1 Summary Measures of Price Responsiveness[7,8] CES Model Specification		
Climate Zone	**Elasticity of Substitution (Weekday Peak to Off-Peak Electricity Use)**	**Price Elasticity for Daily Weekday Electricity Use**
Zone 1	-.032	-.037
Zone 2	-.054	-.027
Zone 3	-.092	-.011
Zone 4	-.111	-.025
All	-.069	-.023

As seen in Table 1-2, the own-price elasticity of demand for peak-period energy use derived from the DL model also varies across climate zones, from a low of –0.055 in climate zone 1 to a high of –0.139 in climate zone 4. The average, statewide value is –0.094. The average cross-price elasticity of demand for peak-period energy use, given a change in off-peak price, equals –0.140, indicating that peak-period energy use will fall with an increase in off-peak prices and vice versa.

Table 1-2 Summary Measures For Price Responsiveness Double-Logarithmic Model Specification[9]			
Climate Zone	**Rate Period**	**Price**	
		Peak	**Off-Peak**
Zone 1	**Peak**	-.055	-.077
	Off-Peak	-.001	-.127
Zone 2	**Peak**	-.077	-.116
	Off-Peak	+.006	-.146
Zone 3	**Peak**	-.116	-.183
	Off-Peak	+.016	-.172
Zone 4	**Peak**	-.159	-.206
	Off-Peak	+.014	-.139
All	**Peak**	-.094	-.140
	Off-Peak	+.009	-.151

7 The values presented in this table are based on average treatment-period weather across all weekdays. The values will differ slightly on CPP and non-CPP days due to differences in average weather on these two day types. The variation across day types compared with the value based on average weather is typically in the range of ±10 percent. Values for each day type are presented later in this report.

8 Determining the statistical significance of these summary variables is complex because they are comprised of three terms in the regression model (e.g., the price term by itself as well as the two interaction terms described in the text). Each of these terms by itself is statistically significant at the 95 percent confidence level. We will provide confidence bands in the Final Impact Evaluation report from the SPP.

9 See footnotes 7 and 8.

1. Executive Summary

The average own-price elasticity of demand for off-peak energy use is -0.151. The zone-specific values range from a low of -0.127 in zone 1 to a high of -0.172 in zone 3. The cross-price elasticity of demand for off-peak energy use as a function of peak period price is quite small, with the statewide average only around +0.01.

Table 1-3 summarizes the impact of the average SPP CPP-F rate on energy use in each rate period on CPP and non-CPP weekdays and on weekends. The vast majority of the difference in impacts on CPP and non-CPP weekdays is due to differences in prices on those days. A much smaller influence is the difference in weather on these days. The underlying demand model indicates that responsiveness varies across days due to differences in weather, with responsiveness being higher on hotter days than on cooler days. For example, compared with the statewide average reduction in peak-period energy use on CPP days of –12.50 percent, the reduction on the hottest two CPP days during the summer 2003 period equals –13.49 percent and equals –10.59 percent on the coolest two CPP days.

As seen in Table 1-3, the reduction in peak-period energy use resulting from the SPP tariffs ranges from a low of –8.35 percent in climate zone 1 to a high of –17.13 percent in zone 4. The statewide average reduction equals –12.50 percent. Off-peak energy use on CPP days increases slightly in three out of four zones, with the statewide increase equaling +3.04 percent.

The change in peak-period energy use on non-CPP days is roughly 60 percent less than the change on CPP days, with a statewide average reduction of –4.80 percent. The difference in percent impacts between CPP and non-CPP days varies across climate zones. For example, in zone 1, the non-CPP day reduction is about 80 percent less than the CPP day reduction while in zone 4, the difference is roughly 40 percent. The increase in off-peak energy use on non-CPP days and weekend energy use is comparable to what it is on CPP days is roughly 2 percent statewide.

Weekend energy use, which accounts for approximately one third of total summer residential energy use, increased by roughly 2.9 percent as a result of the lower off-peak prices associated with the average SPP rate. Across all days, the SPP rates were essentially energy neutral, with an average increase of only 0.01 percent.

Table 1-3 Impact Estimates For Average CPP-F SPP Tariff									
Climate Zone	Impact Measure	CPP Day			Non-CPP Weekday			Weekend/Holiday	Average Summer Day[10]
		Peak	Off-Peak	Daily	Peak	Off-Peak	Daily		
Zone 1	Base Use (kWh/hr)	0.49	0.46	0.47	0.48	0.46	0.46	0.58	0.50
	Change (kWh/hr)	-0.04	0.00	-0.01	-0.01	0.00	0.00	0.00	0.00
	% Change	-8.35	-0.12	-1.94	-1.91	0.82	0.23	0.04	-0.04
Zone 2	Base Use (kWh/hr)	0.84	0.63	0.68	0.78	0.61	0.65	0.88	0.72
	Change (kWh/hr)	-0.08	0.01	-0.01	-0.03	0.01	0.00	0.01	0.00
	% Change	-9.61	1.30	-1.53	-3.32	1.29	0.12	1.56	0.50
Zone 3	Base Use (kWh/hr)	1.65	0.95	1.10	1.45	0.88	0.99	1.26	1.08
	Change (kWh/hr)	-0.22	0.05	-0.01	-0.08	0.02	0.00	0.06	0.02
	% Change	-13.37	4.80	-0.90	-5.59	2.44	0.01	4.41	0.01
Zone 4	Base Use (kWh/hr)	2.02	1.15	1.33	1.79	1.06	1.21	1.53	1.32
	Change (kWh/hr)	-0.35	0.05	-0.03	-0.12	0.03	0.00	0.06	0.02
	% Change	-17.13	4.77	-2.14	-6.83	3.07	0.02	4.05	0.01
All Zones	Base Use (kWh/hr)	1.16	0.76	0.84	1.05	0.72	0.79	1.02	0.86
	Change (kWh/hr)	-0.15	0.02	-0.01	-0.05	0.01	0.00	0.03	0.01
	% Change	-12.50	3.04	-1.42	-4.80	1.95	0.07	2.89	0.01

[10] Averages across all weekdays and weekends during the summer treatment period.

The analysis of the CPP-F rate also examined whether price responsiveness varies with customer characteristics. Key findings include:

- The differential impact of central air conditioning ownership on peak-period energy use is quite small. On a statewide basis, households with central air conditioning reduce load by 12.8 percent and those without air conditioning reduce load by 12.3 percent. This overall impact is the result of two countervailing factors. The elasticity of substitution from the CES specification is actually 50 percent higher for households with air conditioning compared to those that don't have air conditioning. However, the price elasticity of daily energy use is actually smaller for households with air conditioning than for households that don't have air conditioning. The net effect is close to zero.

- High users are significantly more price responsive than low users. For households that use twice the statewide average energy consumption, the reduction in peak-period demand on CPP days is 17.22 percent whereas households that use half the statewide average amount of energy reduce peak-period energy use by only 9.70 percent, a difference of nearly 75 percent.

- High income households are more price responsive than low income households. The reduction in peak-period energy use is 25 percent higher for households with an annual income of $100,000 than for households with an annual income of $40,000.

- Single family households are more price responsive than multi-family households, with single family households showing 37 percent more reduction in peak-period energy use than multi-family households.

- Households living in larger homes are more price responsive than households living in smaller homes. A typical household with a four bedroom home reduces peak-period energy use on CPP days by 14.5 percent whereas a household living in a two bedroom home reduces energy use by only 11.5 percent.

- The reduction in peak-period energy use for households with swimming pools is almost 60 percent greater than for households without swimming pools.

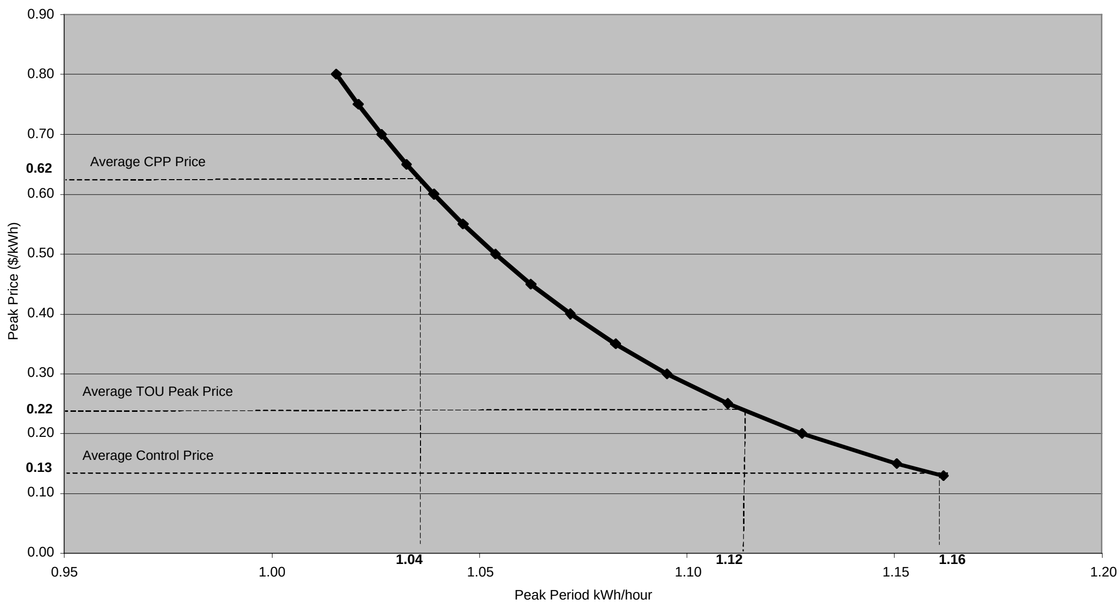
Table 1-4 summarizes the impacts resulting from the average TOU SPP tariff. These results were obtained using the demand model derived from the CPP-F treatment group. Models estimated using the TOU treatment data were generally not credible, due perhaps to the much smaller samples that were drawn for the TOU rate treatment. Based on the detailed analysis summarized in section 5.2, we recommend that the CPP-F demand models be used to predict the impact of TOU rates. The price elasticities underlying the impact estimates in Table 1-4 vary slightly from those underlying the impacts in Table 1-3 due to differences in weather on the average weekday relative to weather on CPP and non-CPP days separately. As seen in the table, the peak-period reduction equals –4.12 percent. This is more than offset by the increase in energy use during off-peak weekdays and weekend periods. The overall increase in energy use resulting from the SPP TOU rates is 0.75 percent.

Table 1-4
Impact Estimates For Average TOU SPP Tariff

Climate Zone	Impact Measure	Peak	Off-Peak	Daily	Weekend	Average Summer Day
Zone 1	Base Use (kWh/hr)	0.49	0.46	0.46	0.58	0.50
	Change (kWh/hr)	-0.01	0.00	0.00	0.00	0.00
	% Change	-1.76	0.79	0.23	0.03	0.16
Zone 2	Base Use (kWh/hr)	0.79	0.61	0.65	0.88	0.72
	Change (kWh/hr)	-0.02	0.01	0.00	0.01	0.00
	% Change	-2.82	1.18	0.16	1.14	0.52
Zone 3	Base Use (kWh/hr)	1.48	0.89	1.01	1.26	1.08
	Change (kWh/hr)	-0.07	0.02	0.00	0.04	0.01
	% Change	-4.84	2.21	0.06	2.97	1.08
Zone 4	Base Use (kWh/hr)	1.82	1.07	1.23	1.53	1.32
	Change (kWh/hr)	-0.11	0.03	0.00	0.03	0.01
	% Change	-5.86	2.72	0.07	2.28	0.84
All Zones	Base Use (kWh/hr)	1.06	0.72	0.79	1.02	0.86
	Change (kWh/hr)	-0.04	0.01	0.00	0.02	0.01
	% Change	-4.12	1.76	0.11	1.91	0.75

The change in energy use given a change in price can be summarized by a demand curve, which is a graphical depiction of the demand model underlying the impact estimates presented in Tables 1-3 and 1-4. Figure 1-3 shows how energy use in the peak period varies with peak period price, other things equal. It corresponds to the CPP-F rate demand model. The curve shows the combined impact of the elasticity of substitution and the daily price elasticity of demand. It should be noted that a number of factors are held constant along the curve. If any of these factors change, such as weather , the saturation of air conditioning or off-peak prices, the curve will shift to the left or right, depending upon the nature of the change in the underlying factors. The curve will shift to the right, for example, as the weather heats up.

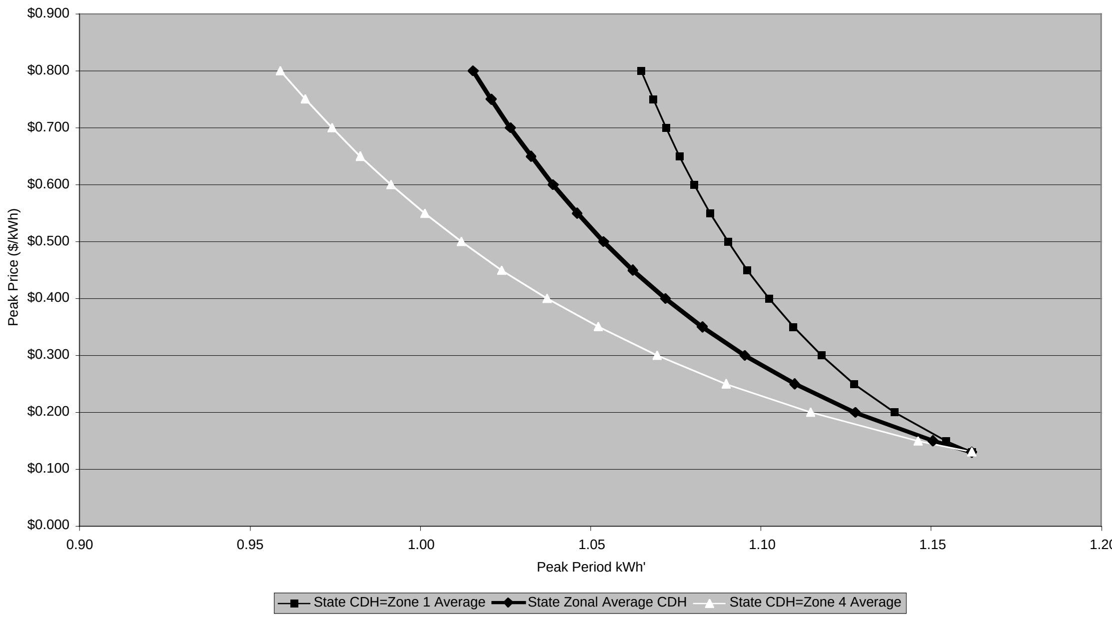
Figure 1-3
Statewide Peak-Period Energy Demand



The demand curve shows that at a price of 13 cents/kWh, which is the approximate price facing the control group and the price that the treatment customers faced in the pre-treatment period, electricity use is 1.16 kWh/hour during the peak period. At a price of 22 cents/kWh, corresponding to the average TOU peak-period price, demand falls to 1.12 kWh/hr. Thus, a rise in the price of 69.23% produces a drop in electricity use of 3.45%, yielding an implicit arc own-price elasticity of demand of -0.050 (= -3.45%/+69.23%). When the price increases to 62 cents/kWh, corresponding to the average CPP peak-period price on CPP days, demand falls to 1.04 kWh/hr. Thus, a rise in the price of 377% from the initial value of 13 cents/kWh produces a drop in electricity use of 10%, yielding an implicit arc own-price elasticity of demand of –0.027. The arc elasticity falls with rising prices, indicating the non-linear nature of price responsiveness.

Figure 1-4 shows the influence of weather on the slope of the demand curve. Hotter weather conditions produce a flatter, more price-responsive demand curve and cooler weather conditions produce a steeper, less-price responsive demand curve. These movements represent a change in the curvature of the demand curve, and arise because of non-linearities in the demand function. These movements should be distinguished from a leftward or rightward shift of the demand curve mentioned earlier, which leave the curvature of the curve unchanged.

Figure 1-4
Peak Period Demand Curves, Default and Weather Variations, Statewide



As discussed previously, in addition to the CPP-F and TOU tariffs summarized above, the SPP also tested a CPP-V tariff. This tariff has a variable-length CPP period with shorter lead times for notification of CPP events. In addition, each customer has a smart thermostat that automatically adjusts the central air conditioner during CPP events. This treatment was tested in the San Diego service territory only and participants are primarily located in climate zone 3 in San Diego (which tends to be a bit milder than the statewide climate zone 3). All consumers on this tariff have central air conditioning and live in single family households with monthly usage greater than 600 kWh. Both treatment customers and the control group with which they are compared had previously volunteered to be in the AB970 Smart Thermostat pilot. Thus, the results from this treatment are not directly comparable to those for the CPP-F tariff and they cannot be generalized to the population at large.

The elasticity of substitution based on the CPP-V treatment is significantly larger on CPP days than on non-CPP days. The average value on CPP days is –0.204 whereas the non-CPP day value is –0.012. The CPP-day value is more than twice the size of the statewide zone 3 value for the CPP-F tariff and nearly three times the statewide, all zone average of –0.069. The price elasticity for daily energy use from the CPP-V treatment is –0.302 on CPP days and –0.258 on non-CPP days. Both of these values are much higher than for the CPP-F tariff. The CPP-V values represent the combined impact of the enabling technology automated response and price-induced behavioral impacts.

Table 1-5 summarizes the own- and cross-price elasticities from the double-log model specification. The own-price elasticity for peak-period energy use on CPP days is more than twice the statewide average for the CPP-F rate and nearly 90 percent larger than the statewide zone 3 value.

Table 1-5
Summary Measures For Price Responsiveness For CPP-V Tariff
Double-Log Model Specification[11]

Day Type	Rate Period	Price	
		Peak	Off-Peak
CPP	Peak	-0.219	-0.203
	Off-Peak	+0.010	-0.021
Non-CPP	Peak	-0.039	-0.264
	Off-Peak	+0.089	-0.063

The average reduction in peak-period energy use per hour from the CPP-V tariff on CPP days is 34.5 percent. Off-peak energy use also falls on CPP days, by 6.6 percent. The non-CPP day reductions in peak and off-peak energy use are much smaller, equaling –2.03 percent and 1.07 percent, respectively. Independent analysis of load shapes carried out by the California Energy Commission suggests that the reduction in peak-period energy use on CPP days attributable to the smart thermostat technology alone amounts to roughly half of the total reduction attributable to the CPP-V rate when it is offered in conjunction with the smart thermostat program. This would suggest that of the total reduction of 34.5 percent cited above, about 17.25 percent is due to the smart thermostat technology by itself and another 17.25 percent due to the behavioral responses triggered by the tariff.[12]

Responsiveness varies with weather for the CPP-V tariff. Based on the weather conditions on the two CPP days that had the highest statewide system load in the summer of 2003, the reduction in peak-period energy use is estimated to equal 39.42

[11] See footnotes 7 and 8.

[12] The SPP featured three cells for customers on the CPP-V rate. One was a control group with the standard (inverted tier, non time-varying) rate. Another group was on the smart thermostat program but on the standard rate. A third group was on the smart thermostat program and on the CPP-V rate. The analysis carried out by the California Energy Commission found that the second group, when compared with the first, had a drop of 23 percent in peak energy consumption while the third group, when compared with the first, had a drop of 48 percent in peak energy consumption. For additional details, consult Pat McAuliffe and Arthur Rosenfeld, “Response of Residential Customers to Critical Peak Pricing and Time-of-Use Rates During the Summer of 2003,” California Energy Commission, September 23, 2004.

percent. On the two CPP days with the lowest statewide load, the reduction in peak-period energy use was 23.34 percent. However, the two CPP days with the highest statewide system load were not the warmest days in San Diego's service territory. If the weather for the two hottest CPP days in San Diego is used, the peak-period reduction in energy use is 47.42 percent.

1.2 KEY FINDINGS FOR C&I CUSTOMERS

Two tariffs were examined for the C&I customer segment, a two-part TOU rate and a CPP-V rate. These rates were tested in the SCE service territory only. The treatment and control populations were divided into two segments, one consisting of consumers with peak demand below 20 kW (LT20) and the other consisting of consumers whose peak demands are between 20 and 200 kW (GT20). The TOU rate was applied to a treatment group drawn from the general target population whereas the CPP-V population was drawn from a group of consumers who had previously volunteered to participate in the AB970 Smart Thermostat pilot. The CPP-V treatment and control customers all have central air conditioning and have been provided with a thermostat that is automatically dispatched during the critical pricing period on CPP days.

The primary conclusions for the sample of CPP-V customers with demands less than 20 kW are as follows:

- The LT20 customer segment shows a significant amount of price response, with the peak-period own-price elasticity equal to –0.18 and the off-peak, own price elasticity equal to -0.22. The cross-price elasticities are small and statistically insignificant.
- The elasticity of substitution for the LT20 customer segment equals -0.15 and the daily price elasticity equals -0.12.
- There is no statistically significant difference in price responsiveness on CPP and non-CPP days, in spite of the fact that the enabling technology for control customers was dispatched at the same time as that of treatment customers on nine of the 12 CPP days.
- Price responsiveness is less for high use customers than for low use customers within the LT20 customer segment
- Price responsiveness is higher on hot, high-system load days than it is on cooler, low-system load days, with the elasticity of substitution being roughly one third larger on high-system load days than on low-system load days.
- The average reduction in peak-period loads on CPP days for LT20 customers attributable to the average SPP rate is roughly 20 percent.

With regard to the GT20 customer segment, inconclusive results were found. This may be an accurate finding or it may be the result of some problem with the sample or the sample data, as some anomalous results were found for the response on non-CPP days (e.g., a positive and significant elasticity of substitution, indicating that customers increase their use during the peak period when prices increase). In this case, we recommend that readers use price elasticities from the literature.

No statistically significant price response was found for the TOU rate treatment for either the LT20 or GT20 customer segments. In this case as well, we recommend that readers use price elasticities from the literature.

Table 1-6[13]
Price Elasticity Estimates For CPP-V Rate Treatment For C&I Customers

Customer Segment	Rate Period	Peak Price	Off-Peak Price	Elasticity of Substitution	Daily Price Elasticity
LT20	**Peak**	**-0.18**	-0.03	**-0.15**	**-0.12**
	Off-Peak	-0.02	**-0.22**		
GT20[14]	**Peak**	**-0.15**	**-0.40**	**-0.05**	**-0.16**
	Off-Peak	-0.02	**-0.21**		

13 Values in bold are statistically significant at the 95 percent confidence level.
14 See the discussion in text regarding the recommendation against using the estimates for the GT20 customer segment for policy analysis.

2. Background and Overview of Experimental Design

2.1 INTRODUCTION

One of the lessons gleaned from California's energy crisis in 2000/2001 is that the lack of demand response in retail markets makes it very difficult to equilibrate wholesale markets at reasonable prices.[15] In the absence of demand response, the normally downward sloping demand curves become vertical, since customers do not change their demand for electricity in response to changes in the wholesale price of electricity. Studies have shown that economic efficiency in the allocation of scarce capital, fuel and labor resources can be realized by introducing demand response in retail markets. One method for introducing demand response in retail markets is time-varying pricing. With this in mind, the California Public Utilities Commission (CPUC) initiated a proceeding in July 2002 designed to introduce demand response in California's power market.[16]

As part of this proceeding, three working groups were charged with developing specific tariff proposals to achieve increased demand response in the state. The mission of Working Group 3 (WG3) was to develop a dynamic tariff (or set of tariffs) for residential and small commercial customers with demands less than 200 kW. WG3 included representatives from the state's three investor-owned utilities[17], commissions, equipment vendors, The Utility Reform Network (TURN) and other interested parties.

As part of the WG3 deliberations, Charles River Associates (CRA) conducted a preliminary analysis of the potential benefits of a variety of time-differentiated rates at Pacific Gas & Electric Company (PG&E). The analysis included static time-of-use (TOU) rates and dynamic rates where high price signals are passed through to consumers on selected days when supply is constrained, the timing of which is unknown. The analysis showed a wide range of potential benefits from the implementation of dynamic pricing at PG&E, with the lower end being $561 million and the high end being $2,637 million. Incremental metering and billing costs associated with the provision of dynamic pricing were estimated at about a billion dollars. Consequently, there is a wide range in estimates of the potential net-benefits of dynamic pricing, depending upon assumptions about meter and rate deployment strategy and costs, the level of customer demand response and the magnitude of avoided energy and capacity costs. Analysis also indicated that conducting an experiment with a few thousand customers could significantly reduce the uncertainty in the net benefit estimates.

Based in part on this preliminary analysis, WG3 recommended on December 10, 2002 that the state conduct a carefully designed social experiment with different pricing

15 James L. Sweeney, The California Electricity Crisis, Hoover Institution Press, 2002.

16 Order Instituting Rulemaking on policies and practices for advanced metering, demand response and dynamic pricing, R. 02-06-001.

17 Pacific Gas & Electric (PG&E), San Diego Gas & Electric (SDG&E) and Southern California Edison (SCE).

options prior to making a decision on full-scale deployment of the automated metering infrastructure required to support such rates. It was decided to go with a statewide experiment rather than utility-specific experiments to better leverage scarce budget resources and also to ensure consistency in results across the state. The CPUC approved the experiment, now called the Statewide Pricing Pilot (SPP), on March 14, 2003.[18]

The SPP has three primary objectives:

- Estimate average demand impacts and demand curves for electricity consumption by time-of-use period for dynamic tariffs and derive the associated price elasticities of demand
- Determine customer preferences for tariff attributes and market shares for specific TOU and dynamic tariffs, control technologies and information treatments under alternative deployment strategies
- Evaluate the effectiveness of and customer perceptions of specific pilot features and materials, including enrollment and education material, bill formats, web information, and tariff features.

This report primarily addresses the first objective for the period of time from customer enrollment through the end of the summer 2003 period. Separate reports will address the second and third objectives.

This report is an update and extension of a previous draft that was issued on March 9, 2004. All previous results pertaining to the residential CPP-F, CPP-V and TOU results in Sections 4 and 5 of that report should be discarded and replaced with the estimates presented in Section 5 of this report. This report also presents for the first time results for small commercial and industrial customers.

There are several reasons why the previous results are no longer valid. They suffered from the effects of autocorrelation and heteroscedasticity in the error term and the demand models were based on used sample data that was unweighted by population means. We have remedied these problems in this report by the inclusion of population weights, averaging the daily data, including pre-treatment data in the regression models and combining the CPP and non-CPP days in the same model. Additionally, we have pooled data across climate zones and estimated the impact of customer characteristics on price responsiveness.

Based on these procedures, we have developed demand models for estimating price elasticities and elasticities of substitution. These models have been used to estimate the impact of time-varying rates on energy use by period, rather than relying on a separate class of models based on the difference-in-differences approach used previously.

[18] Decision 03-03-036, Interim Opinion in Phase 1 adopting pilot program for residential and small commercial customers.

2 Background and Overview of Experimental Design

We have not updated the coincident peak demand models since we now believe the relevant measure from a cost-effectiveness perspective is the impact on peak demand during the top 60 to 75 hours of the year rather than the impact on the single maximum load hour. The impact on the top 60-75 hours can be derived from the impact on energy used during the peak period on CPP days. This energy impact is of course the impact on average demand during the critical peak period. We have performed some side calculations and found that the average demand during the five hour critical peak period is highly correlated with the coincident peak demand.

This report includes all of Section 2 on sample design and portions of Section 3 on data development from the March 9th report. Section 4 of this report describes the impact estimation methodology. Section 5 presents residential results and section 6 presents results for the commercial and industrial customer segment.

The tariffs being tested in the SPP include a traditional TOU rate and two types of dynamic pricing rates. The dynamic rates include a critical-peak pricing (CPP) element that involves a substantially higher peak price (about 50 to 75 cents/kWh) for 15 days of the year and a standard TOU rate on all other days. One type of CPP rate (CPP-F) features a fixed peak period on both critical and non-critical days and day-ahead customer notification. The peak period for residential customers is between 2 pm and 7 pm weekday afternoons and the peak period for commercial and industrial customers is from noon to 6 pm. The other type of CPP rate (CPP-V) features a variable-length peak period on critical days, which may be called on the day of an “emergency.” All SPP rates are seasonally differentiated, with summer running from May through October, inclusive, for residential customers and from June through October 5th for commercial and industrial customers.[19]

In addition to the rate treatments described above, an “Information Only” treatment was also tested for residential customers. This treatment involves notifying customers on CPP days and asking them to avoid energy use during the peak period. However, prices do not change on CPP days for these customers and the customers do not face time-varying prices on any day.

Residential customers in the SPP are divided into four climate zones and commercial/industrial customers into two size strata, very small (< 20 kW demand) or small (between 20 and 200 kW demand). Residential customers are drawn from the service territories of all three participating utilities (PG&E, SDG&E and SCE) while the commercial/industrial customers are drawn exclusively from SCE. The customers are divided into three tracks:

- Track A represents the general population of customers in the state.
- Track B represents the population of relatively low-income customers living in the vicinity of two power plants in the Hunters Point/Potrero division of San Francisco

[19] Small commercial and industrial customers are only in the SCE service territory and their summer period ends on October 5.

and a control group of customers in the city of Richmond. All these customers reside in the PG&E service area.[20]

- Track C represents the population of customers who had previously volunteered to be in the AB970 Smart Thermostat pilot program in the SCE (small commercial and industrial customers only) and SDG&E (residential customers only) service areas.

The revised overall sample design consists of 2,504 customers of which 850 are control customers and 1654 are treatment customers. A total of 1790 customers are in Track A, 253 customers are in Track B and 461 customers are in Track C.[21]

The remainder of this section discusses rate design, sample design and customer enrollment issues. Section 3 summarizes the analytical methods and data that were used to estimate the energy and demand impacts attributable to the SPP treatments. Section 4 summarizes the demand modeling and impact evaluation results for the residential sector in Tracks A and C while section 5 presents the C&I results. The appendices, presented in a separate volume, contain a wide variety of technical details as well as the regression results underlying the information presented in sections 4 and 5.

2.2 RATE DESIGN

The specific tariffs that are being tested in the SPP reflect compromises among WG3 members concerning the rate options that it would be desirable to explore, numerous analytical complexities, historical differences across service territories, and several political realities.

2.2.1 CUSTOMER PROTECTION CONSTRAINTS

The CPUC placed a number of constraints on the rate design process in order to address the concerns of various constituencies within WG3. Specifically, the experimental rates were required to satisfy three constraints:

- be revenue neutral for the class-average customer over a calendar year, in the absence of any change in the customer's load shape,

[20] Results from Track B will be presented in a separate report.

[21] The original sample design included a total of 2,591 customers (1741 treatment and 850 control customers) of which 1,877 were assigned to track A, 253 to track B and 461 to track C. In early June, recruitment efforts were halted for the CPP-V, track A cells due to poor take rates; this resulted in revising the target number of customers downward (as reflected in the revised target numbers) to reflect actual enrollment in the Track A cells for which recruitment was terminated. Research on the reasons underlying the slow take rates for Track A is summarized in Focus Pointe, "Statewide Pricing Pilot: Enrollment Refusal Follow-up Research," November 2003.

- not change the bill of low and high users by more than 5% in either direction, in the absence of any change in the load shape, and

- provide customers with an opportunity to reduce their bills by 10% if they reduced or shifted peak usage by 30%.

An additional design constraint, suggested by one of PG&E's rate analysts, was to lower bills when price ratios are high and raise bills when price ratios are low, in order to minimize adverse bill impacts for low and high users. Condition (a) was satisfied by placing customers on a high price ratio in the summer and a low price ratio in winter. The rates are revenue neutral on an annual basis, but not on a seasonal basis. The other conditions were satisfied by testing a variety of price ratios.

Finally, it is important to note that low-income households qualify for a 20% discount of their electricity bill under a program called CARE. For example, maximum eligible income for a CARE household can be no higher than $23,000 with one or two persons in the household; and no higher than $43,500 for a household with six persons. The manner in which the 20% CARE discount is passed on to customers varies by utility.

2.2.2 EXPERIMENTAL CONSIDERATIONS

The experimental rates are designed to allow estimation of the own and cross-price elasticities of demand for electricity by time-of-use period.[22] Each time-varying rate consists of two pricing periods, peak and off-peak. As such, there are two own-price and two cross-price elasticities associated with each tariff. In order to estimate all four price elasticities, two rate levels were created for each treatment group. When combined with the non-time varying rate for the control group, this yields three price points along the demand curve for energy use in each time period. In order to estimate a statistically valid demand function, it is necessary that the tariffs not be revenue neutral. If they were revenue neutral, there would be perfect collinearity in the price terms, rendering the models statistically unidentifiable.

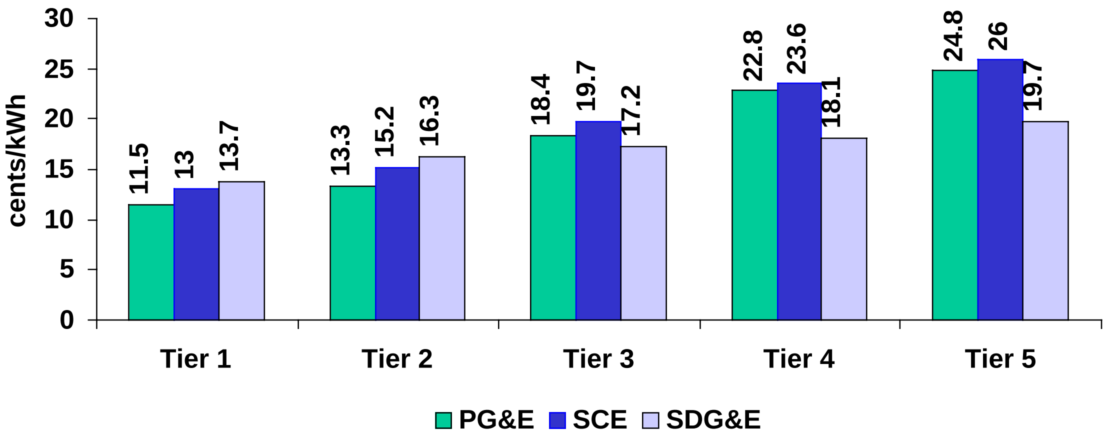
Another rate-related complication was the existence of different base rates across the three utilities. The average annual rate, expressed in cents/kWh and measured in January 2003, was 12.5 for PG&E, 13.5 for SCE and 14.5 for SDG&E.[23] Prices during the summer were 12.7 for PG&E and, rounded, 14.1 for both SDG&E and SCE. As shown in Figure 2-1, the inverted five-tier rate structure differs across the utilities. SDG&E customers start out with a higher price in Tier 1 but their prices don't rise as steeply as they do for PG&E and SCE customers. Thus, customers in SDG&E's service

22 In this context, the own price elasticity of demand equals the ratio of the percentage change in energy use in a period (say the peak period) over the percentage change in price in the same period. The cross-price elasticity of demand equals the percentage in usage in one period (say the peak period) divided by the percentage change in the price of energy in another period (say the off-peak period).

23 The average values in Figure 2-1 differ from those in Figure 1-1 because those in Figure 1-1 represent Tier-3 customers whereas those in Figure 2-1 represent the average customer across all tiers.

territory pay slightly less than 20 ¢/kWh for Tier 5 usage whereas Tier 5 customers in PG&E's service area pay roughly 24.5 ¢/kWh and in Edison's they pay 26 ¢/kWh.[24]

Figure 2-1
Marginal Prices For Control Group Customers
At Start Of Treatment Period



In developing rates for each utility, a decision was made to expose customers to consistent price differentials by time-of-day while maintaining the differences in the underlying rates across utilities. This approach applies a set of time-varying surcharges and discounts on top of the existing rate structure of each utility. The surcharges and discounts are identical across utilities, causing the effective TOU and CPP prices to differ by small amounts because of the differences in the underlying rates. This approach, which preserves the inverted character of the underlying rate structure, was chosen over an alternative approach that would have used a flat base rate for all consumers, with a time-varying rate structure applying to treatment customers. The primary disadvantage of the second approach is that it would have provided a substantial bill discount to high usage customers relative to low usage customers. As such, many high-usage customers would have displayed a strong preference for the time-varying rate because it would lower their average rate even in the absence of changing their usage patterns or levels. In addition, the chosen approach automatically reflects changes in the underlying base rates that might occur during the experiment due to the normal course of business by each utility.[25] The alternative approach would have required filing new experimental tariffs every time the underlying tariff changed and was not pursued for this and other reasons.

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24 Edison's rates fell shortly after the pilot started, especially the Tier 5 marginal price, which is now equal to roughly 17 ¢/kWh. All tariff changes that were made by each utility during the course of the experiment were passed through to both treatment and control customers so rates will vary over time.

25 Indeed, SCE implemented a significant rate reduction shortly after customers went on the rate.

Given the complex nature of customer bills, customers are being provided with a summary sheet showing (a) how much electricity they used during the billing cycle period by pricing period, (b) how much they paid for it and (c) the implicit price for each period, expressed in cents per kWh. At the beginning of the experiment, customers were also provided a shadow bill that projected their likely electric bill on the experimental tariff during the summer and winter months and compared it with what their bill would have been had they stayed on their existing tariff under different assumptions about the magnitude of load shifting. Customers will also be provided with another shadow bill after having been in the experiment for twelve months. Finally, customers can request a shadow bill anytime during the experiment. Appendix 1 contains an example of a filed tariff, a summary sheet and a shadow bill.

2.2.3 CRITICAL PEAK DISPATCH

Dispatch of the CPP rates was based on a variety of criteria. First, about half the time, CPP-F and CPP-V rates were dispatched simultaneously. Second, for residential CPP-V Track C customers, the length of the dispatch period on CPP event days was either two hours or five hours. For C&I, CPP-V customers, two, four and five hour dispatch periods were implemented over the summer. Finally, to minimize customer discomfort, no more than five events were called in any month and no more than two events per week. A total of 12 events were called for each treatment in the summer months (May to October) and three are planned to be called in the winter. Critical days were chosen based on weather forecasts, system reliability conditions, the need to have a total of 12 days in the summer and to have a variety of days in the week. Table 2-1 summarizes the CPP events that occurred during the summer 2003 rate period.

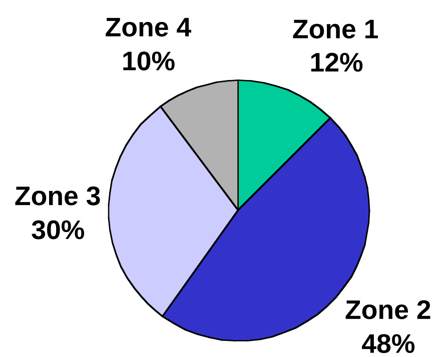
Table 2-1
CPP Event Day Summary

Zone	July			August					September						October		
	7/10	7/17	7/28	8/8	8/14	8/15	8/18	8/27	9/3	9/11	9/12	9/19	9/22	9/29	10/9	10/14	10/20
Residential CPP-F Rate Treatment																	
1	X	X	X				X	X	X	X	X		X		X	X	X
2	X	X	X	X			X	X	X		X		X		X	X	X
3	X	X	X	X			X	X	X		X		X		X	X	X
4	X	X	X	X			X	X	X		X		X		X	X	X
Residential CPP-V Rate Treatment																	
3	2-4	2-4	2-7	3-5		2-7	4-6	2-7	2-7		2-7			2-7	3-5	2-7	3-5
C&I CPP-V Rate Treatment																	
SCE	2-4	2-4	1-6	3-5	1-6	2-6		4-6	1-6	1-6	4-6	4-6		1-6			

2.3 SAMPLE DESIGN

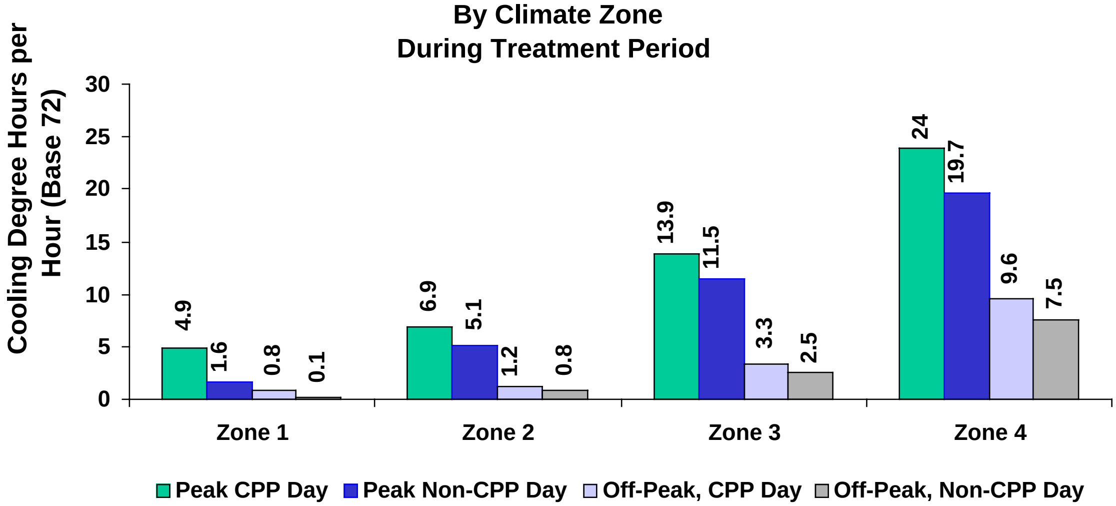
To capture the diversity in California's climate, and to allow customer response to time-varying rates to vary with climate, the SPP experimental design segments customers into four climate zones. As seen in subsequent sections, impact estimates are presented for each climate zone. Figure 2-2 shows the distribution of utility customers across zones. About 48% of the population of the three utilities resides in the relatively moderate climate zone 2, 40% resides in the hotter zones 3 and 4 and 12% resides in the temperate zone 1. Maps of the climate zones and the distribution of the SPP sample within the climate zones appear in Appendix 2.

Figure 2-2
Distribution Of Population Across Climate Zones



Roughly 60 weather stations have been used across all climate zones to capture the rather significant number of microclimates that exist in California. The average cooling-degree hour per hour values for each climate zone presented in Figure 2-3 represent population-weighted averages based on the weather stations applicable to each climate zone. A list of the weather stations and their populations is contained in Section 3.2.4 of this report.

Figure 2-3
Average Daily Cooling Degree Hours Per Hour
By Climate Zone
During Treatment Period



2 Background and Overview of Experimental Design

Bayesian sampling techniques were used to allocate sample points to each of the various cells in the SPP.[26] In brief, this approach allocates more sample points to cells where prior analysis indicates that the net benefits are potentially large but uncertain and fewer sample points to those cells with small or certain net benefits. The outcome of this sampling approach was that CPP-F and CPP-V cells received the largest sample allocations. Table 2-2 summarizes the original sample allocation resulting from application of the Bayesian approach in combination with judgment regarding coverage for selected cells that the Bayesian analysis otherwise would have excluded.

[26] Details are presented in the December 10, 2002 report of WG3.

Table 2-2
Sample Design of the Statewide Pricing Pilot

	Control	CPP-F	CPP-F (info)	CPP-V (SDG&E) (1)	Info Only (1)	TOU	Total
Track A: Random Sampling With Opt Out Design							
Residential							
Zone 1	63	52	0	0	0	50	165
Zone 2	100	188	0	0	0	50	338
Zone 3	207	188	0	125	126	50	696
Zone 4	100	114	0	0	0	50	264
Total	470	542	0	125	126	200	**1463**
Commercial				**CPP-V (SCE) (1)**		**TOU (SCE) (1)**	
SCE							
<20 kW	88	0	0	58	0	50	196
>20 kW	88	0	0	80	0	50	218
Total	176	0	0	138	0	100	**414**
All Sectors							
Total	646	542	0	263	126	300	**1,877**
Track B: SF Cooperative							
Residential	**Control**	**CPP-F**	**CPP-F (Info)**	**CPP-V**	**Info Only**	**TOU**	**Total**
PG&E (2)	63	64	126	0	0	0	253
Total	63	64	126	0	0	0	**253**
Track C: AB 970 Sub-Sample							
Residential	**Control**	**CPP-F**	**CPP-F (Info)**	**CPP-V (SDG&E)**	**Info Only**	**TOU**	**Total**
SDG&E (3)	20	0	0	125	0	0	145
Total	20	0	0	125	0	0	145
Commercial		**CPP-F**	**CPP-F (Info)**	**CPP-V (SCE)**	**Info Only**	**TOU**	**Total**
SCE (3)							
<20 kW	42	0	0	56	0	0	98
>20 kW	42	0	0	76	0	0	118
Total	84	0	0	132	0	0	216
All Sectors							
Total	104	0	0	257	0	0	361
SUMMARY							
	Control	**CPP-F**	**CPP-F (Info)**	**CPP-V**	**Info Only**	**TOU**	**Total**
TOTAL SAMPLE SIZE	**813**	**606**	**126**	**520**	**126**	**300**	**2491**

All sample Sizes include the provision for 20% Opt-Out.

Notes:

(1) Entries are to be spread across various climate zones.

(2) This row corresponds to a proposal made by the San Francisco Cooperative and will be based on an opt out random sample located in the Hunter's Point/Potrero Hill districts of San Francisco and West Oakland/Richmond.

(3) These customers will be selected on an opt-out basis from the existing AB970 sample, which has an opt-in structure. In addition to the 20 control customers selected specifically for this study, the control group of 100 customers for the AB970 pilot is also being utilized. For any given event, half of these customers receive the dispatch signal and the other half do not. The 50 who do not are used as part of the control group for that event.

2.3.1 Residential Sample Design

Within each cell, the samples were optimized to provide the greatest level of accuracy for the pre-specified Bayesian allocations. After stratifying by housing type, the Dalenius-Hodges method[27] was used to determine optimal usage cut points, and the Neyman allocation method[28], which allocates more sample points to strata with greater variance, was applied to increase the explanatory capability of the final sample. For multi-family strata, the allocated sample sizes were small, so these cells were not segmented further based on the Neyman allocation method. Table 2-3 summarizes the allocation of samples within each cell for the residential CPP-F and TOU rate treatments based on the Dalenius-Hodges and Neyman processes.

Table 2-3
Sample Allocation for Residential Track A CPP-F , TOU, and Control*
By Climate Zone, Dwelling Type, and Usage Level

				Control				CPP-F				TOU			
Climate Zone	Dwelling Type	Usage	Population Count	Total	PG&E	SCE	SDG&E	Total	PG&E	SCE	SDG&E	Total	PG&E	SCE	SDG&E
1	Single	Low	432,173	17	17	0	0	14	14	0	0	13	13	0	0
		High	188,621	21	21	0	0	18	18	0	0	17	17	0	0
	Multiple	All	406,722	25	25	0	0	20	20	0	0	20	20	0	0
			1,027,516	***63***	***63***	***0***	***0***	***52***	***52***	***0***	***0***	***50***	***50***	***0***	***0***
2	Single	Low	1,848,301	27	10	11	6	51	19	21	11	13	6	7	0
		High	814,877	45	23	16	6	85	44	29	11	22	13	9	0
	Multiple	All	1,259,417	28	10	12	6	53	19	23	11	14	6	8	0
			3,922,595	***100***	***43***	***39***	***18***	***188***	***82***	***73***	***33***	***50***	***25***	***25***	***0***
3	Single	Low	1,249,106	32	7	21	4	60	13	40	7	16	4	12	0
		High	675,729	46	14	29	3	87	26	55	6	23	8	15	0
	Multiple	All	533,557	22	5	14	3	41	9	26	7	11	3	8	0
			2,458,392	***100***	***26***	***64***	***10***	***188***	***48***	***120***	***20***	***50***	***15***	***35***	***0***
4	Single	Low	433,556	30	20	11	0	35	22	12	0	15	10	5	0
		High	257,864	49	31	18	0	56	36	20	0	25	16	9	0
	Multiple	All	173,943	20	13	7	0	23	15	8	0	10	7	3	0
			865,363	***100***	***64***	***36***	***0***	***114***	***73***	***41***	***0***	***50***	***33***	***17***	***0***
Total			***8,273,866***	***363***	***196***	***139***	***28***	***542***	***255***	***234***	***53***	***200***	***123***	***77***	***0***

Table 2-4 summarizes the shares represented by each strata in the sample and control group populations. As indicated there, the primary outcome of the sample allocation process described above is that high usage customers constitute a larger share of the SPP sample than they do in the population at large. The impact estimates and demand models presented in sections 4 and 5 have been adjusted to reflect differences between the sample and population shares based on the stratification variables.

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27 The Dalenius-Hodges procedure generates optimal stratification boundaries for a fixed number of strata within a homogenous population. Boundaries are optimal in the sense that the variance of the estimate for a given population parameter is minimized. Notice, in this instance, we are actually using this technique to define a set of homogeneous sub-populations. Usually the stratifying variable (as is the case for this sample design) is a proxy value for the population parameter of interest. On-peak demand is not known for residential customers thus a proxy (summer average daily usage) was used.

28 Neyman Optimal allocation technique assigns sampling points to each stratum based on the percentage of the total population standard deviation of the parameter of interest represented by the stratum. Neyman allocation optimizes the fixed sample size. .i.e. maximizes the precision. In practice, this technique tends to disproportionately allocate sample units to the high energy users because the variance in these strata is very large compared to other strata. The daily average usage was used as a proxy for the parameter of interest (usage during on-peak or CPP period) in Neyman allocation.

Table 2-4 Sample And Population Shares For CPP-F And TOU Control Groups (Shares add to 100% across rows, for sample and population separately)						
Zone	Single Family Low Use		Single Family High Use		Multiple Family	
	Sample	Population	Sample	Population	Sample	Population
1	27.0 %	42.1 %	33.3 %	18.4 %	39.7 %	39.6 %
2	27.0 %	47.1 %	45.0 %	20.8 %	28.0 %	32.1 %
3	32.0 %	50.8 %	46.0 %	27.5 %	22.0 %	21.7 %
4	30.0 %	50.1 %	49.0 %	29.8 %	20.0 %	20.1 %
All	29.2 %	47.9 %	44.3 %	23.4 %	26.2 %	28.7 %

For each stratum, a series of potential samples were selected at random and without replacement. The final sample was chosen so that it most closely resembles the population in terms of summer average daily usage. Several types of customers were excluded from the sampling frame, including those who (a) live in master-metered dwellings and therefore cannot be sent a time-varying price signal, (b) are on a medical baseline rate and may not be able to engage in load shifting without endangering their condition, (c) are on an existing time-of-use (TOU) rate or an air conditioner cycling program, which they have chosen on a voluntary basis, (d) are a direct access customer, who buy power from third party suppliers, (e) are a net metering customer, producing their own power, or (f) get power on standby rates or special contract rates.

Sample allocations for Track B and for the Information Only cells in Track A are contained in Tables 2-5 and 2-6.

Table 2-5 Sample Allocation for Track B By Rate Group and Usage Level											
General Population						Climate Zone 1 Only					
						Info Only		CPP-F			
SPP Track	Rate Group	Location	Dwelling Type	Usage Level	Population Count	Cell ID	Sample Size	Cell ID	Sample Size		
									Total	Rate Treatment	
										High	Low
B	E-1	Hunter's Point	MF	Low	2,580	B01	10				
			MF	High	1,574	B01	13				
			SF	Low	4,588	B01	25				
			SF	High	1,723	B01	15				
					10,465		**63**				
	E-3	Hunter's Point	MF	Low	2,580			B02	20	10	10
			MF	High	1,574			B02	26	13	13
			SF	Low	4,588			B02	50	25	25
			SF	High	1,723			B02	30	15	15
					10,465				**126**	**63**	**63**
	E-3	Richmond	MF	Low	5,827			B03	18	9	9
			MF	High	2,311			B03	6	3	3
			SF	Low	10,946			B03	32	16	16
			SF	High	2,685			B03	8	4	4
					21,769				**64**	**32**	**32**

Table 2-6 Sample Allocation For Track A Standard Tariff Information Only By Rate Group and Usage Level							
General Population							
						Info Only	
SPP Track	Rate Group	Climate Zone	Dwelling Type	Usage Level	Population Count	Cell ID	Sample Size
A	E-1	2	MF	All	407,559	A11	15
			SF	Low	661,508	A11	15
			SF	High	408,776	A11	33
					1,477,843		**63**
	E-1	3	MF	All	100,956	A12	11
			SF	Low	248,319	A12	18
			SF	High	195,122	A12	34
					544,397		**63**

As previously mentioned, the CPP-V treatment was intended to be applied to two different populations, the general population (Track A) and the population of consumers who had already volunteered for the AB970 Smart Thermostat pilot program (Track C). The Track A sample design called for the selection of 125 customers split between climate zones 2 and 3. The selection criterion was that a customer's usage during the summer months must exceed 600 kWh a month. This resulted in a pool of approximately 240,000 customers. Current smart thermostat participants were excluded from Track A. Note that the Track A CPP-V target population included approximately 80,000 customers that were originally solicited for the Smart Thermostat program (climate zone 3 only) and that decided not to opt-into that program. The Track A CPP-V was marketed to both multi and single-family residences that exceeded the threshold of 600 kWh a month.

SDG&E performed an optimal allocation using the Dalenius-Hodges procedure with stratification boundaries on high and low summer average daily usage. The procedure was applied to the target population frame of approximately 240,000. The treatment group consisted of 125 primary sample sites with 20 like replacements for each primary sample site. SDG&E anticipated that recruitment for the CPP-V technology treatment customers would require extensive sample replacements.

For the residential Track C CPP-V treatment group, a random sample of 125 primary sites was selected from SDG&E's population of 3,650 AB970 Smart Thermostat Program Participants. The treatment group customers were placed on a CPP-V rate, with the group being split evenly between the high and low rate differentials. Nearly all of the existing Smart Thermostat participants are located in SDG&E's inland climate zone. SDG&E's inland climate zone is in the statewide climate zone 3, although the weather in San Diego is milder than the average statewide weather in zone 3.

SDG&E utilized an existing sample of 100 Smart Thermostat participants with interval data recorders for its CPP-V Control Group 1. This group of 100 customers was split into two groups of 50. On any given curtailment day, 50 are controlled and 50 are curtailed. SDG&E made these 100 interval metered customers aware that they would be asked to curtail on days other than an ISO stage 2 alert. SDG&E modified the curtailment criteria for its existing smart thermostat control group so that direct comparisons to the treatment group can be made.[29]

SDG&E was able to utilize a control sub-sample from Track A CPP-V. This sub-sample was selected from SDG&E's inland customers (climate zone 3) with more than 600 kWh summer monthly usage. This second control group sample was selected using the Dalenius-Hodges method with a Neyman allocation as described in the prior section. The second control group had initially received the Smart Thermostat Program marketing materials and chose not to participate. Both control group customers were required to have the ability to utilize an enabling technology such as 1-way or 2-way paging.[30]

Table 2-7 summarizes the CPP-V sample allocation.

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29 The ISO Stage 2 trigger remains in effect for these customers and will still be one of the criteria for curtailment with the CPP-V rate.

30 Initially, the smart thermostat program was offered only to customers in SDG&E's inland climate zone whose monthly summer consumption was at least 700 kWh. This resulted in a marketing list of approximately 60,000 customers. SDG&E estimates that 50% of its inland customers have the use of a central air conditioner. Though SDG&E only directly marketed to its inland customers, any residential customer was able to participate if they had central air conditioning. Because initial participation rates were lower than expected, SDG&E reduced the required monthly summer consumption level down to 600 kWh. Lowering the summer monthly kWh threshold resulted in a target-marketing list of approximately 80,000 customers.

Table 2-7
Sample Allocation for Residential Track C, CPP-V Tariff

Climate Zone	Dwelling Type	Usage	Sample	Sample Description	Population	Sample Size Total	Rate Differential High	Rate Differential Low
2	All	Low	CPP-V- Track A	*Treatment Group* (> 600 kWh)	78,335	19	10	9
2	All	High			26,014	43	22	21
3	All	Low	CPP-V- Track A	*Treatment Group* (> 600 kWh)	81,865	21	11	10
3	All	High			30,046	42	21	21
					216,260	***125***	***64***	***61***
2	All	Low	CPP-V- Track A	*Control Group1* (> 600 kWh)	78,335	8	-	-
2	All	High			26,014	18	-	-
3	All	Low	CPP-V- Track A	*Control Group1* (> 600 kWh)	81,865	6	-	-
3	All	High		Also Control 2 for C02	30,046	12	-	-
					216,260	***44***		
2	All	Low	CPP-V- Track A	*Control Group* 2	289,892	8	-	-
2	All	Med		Entire Population Sample Frame	262,788	11	-	-
2	All	High			73,168	17	-	-
3	All	Low	CPP-V- Track A	*Control Group* 2	200,467	7	-	-
3	All	Med		Entire Population Sample Frame	189,059	9	-	-
3	All	High			59,507	11	-	-
					1,074,881	***63***		
3	All	All	CPP-V- Track C	*Treatment Group* - Smart Therm Part Target population > 600 kWh a month	*3,650*	126	62	63
					3,650	***126***	***62***	***63***
3	All	All	CPP-V- Track C	*Control Group 1* (> 600 kWh) Smart Thermostat Participants **	*3,650*	70	-	-
					3650	**70**		
				Total CPP-V Residential Sample	***3,650***	***428***	***126***	***124***

*** This control group utilizes the existing control group for the residential smart thermostat program. 20 Additional sites were selected to complement the existing control group.*

2.3.2 C&I Sample Design

The objective of the C&I portion of the SPP was to evaluate the ability and willingness of small commercial and industrial customers to shift or reduce energy consumption during the peak period. The study's plan was to test two forms of time-varying pricing, dynamic pricing (CPP-V) and static pricing (TOU). For the CPP-V rate, the emphasis is on measuring the ability of customers to reduce/shift their air conditioning loads using an enabling technology (e.g., a "smart" or controllable thermostat). For the TOU rate, the intent of the SPP is to measure the ability of customers to reduce/shift their entire load, and not just their air conditioning load. The C&I samples were designed to achieve these objectives.

The target population of the TOU treatment sample is the general population of C&I customers below 200 kW in the SCE service territory who are likely to have some economic incentive to respond to TOU rates. Very small customers (e.g., daily average usage < 5 kWh) and those who clearly have little or no economic incentive to respond to TOU rates (e.g., bus stops, ATM machines, billboards) were excluded.

The target population for the Track A, CPP-V sample is the general population of C&I customers below 200 kW in the SCE service territory who are likely to have air conditioning and for whom an enabling technology is feasible. When developing the sample, customers were excluded if they did not live in areas with 2-way paging coverage or they did not have enough load to account for air conditioning.[31]

In addition to the treatment groups, two separate control samples were also selected, one from the CPP-V treatment population and one from the population of TOU treatment. As with the residential samples, several types of customers were excluded from the sampling frame, including direct access customers, those on existing TOU rates, those on the air conditioning cycling program, net energy metering customers, and those on standby or special contract rates.

The target population for the Track C sample is C&I customers in SCE's service territory who had already volunteered to participate in the AB970 smart thermostat program.[32] A stratified random sample from this population was selected to recruit for CPP-V rates. A separate blind control sample was also randomly selected from the same population. It is important to keep in mind that the population frame for this sample is by no means a representative sample of the general C&I customers.

In each sample, the total size was first allocated between the two rate groups GS-1 (< 20 kW) and GS-2 (20-200 kW) and then between the treatment rates and control samples using the results from the Bayesian model adjusted to allow for a minimum number in each cell. Stratified random sampling was then applied using size (kW) as the only stratification variable and using standard load research sample design and section methods such as Dalenius-Hodges technique, Neyman optimal allocation, and sample validation. Table 2-8 summarizes the allocation of C&I sample for treatment and control for both tracks A and C.

[31] Those with summer daily usage less than 10 kWh (not enough load for having A/C), pumping and lighting SIC codes were excluded.

[32] The Smart thermostat program had been offered to about 68,000 customers with commercial SIC codes excluding government accounts, schools, all chain-affiliated customers, customers without 13 months of billing history, and those not meeting the summer/winter ratio of 1.2. Because of this and the opt-in nature of this program, this sample is not a representative sample of small C&I population.

Table 2-8
Sample Allocation for Small Commercial & Industrial
(Tracks A and C: TOU, CPP-V, and Controls)
By Rate Group and Design

General Population				TOU						CPP-Variable						
				Control (A)		TOU Treatment					Control (B)		CPP-V Treatment			
							Sample Size							Sample Size		
								Rate							Rate Treatment*	
SPP Track	Rate Group	Usage Level	Population Count	Cell ID	Sample Size	Cell ID	Total	High	Low	Population Count **	Cell ID	Sample Size	Cell ID	Total	High	Low
A	GS-1	Low	229,423	A17	19	A21	22	11	11	142,724	A27	19	A19	24	12	12
		High	84,096	A17	25	A21	28	14	14	56,233	A27	25	A19	34	17	17
			313,519		44		50	25	25	198,957		44		58	29	29
	GS-2	Low	73,788	A18	17	A22	20	10	10	60,994	A28	17	A20	32	16	16
		High	28,539	A18	27	A22	30	15	15	23,389	A28	27	A20	48	24	24
			102,327		44		50	25	25	84,383		44		80	40	40
			415,846		88		100			283,340		88		138		

Smart Thermostat (AB970) program				CPP-Variable						
					Control (3)		CPP-V Treatment			
								Sample Size		
									Rate Treatment*	
SPP Track	Rate Group	Usage Level		Population Count	Cell ID	Sample Size	Cell ID	Total	High	Low
C	GS-1	Low		836	C03	17	C05	22	11	11
		High		408	C03	25	C05	34	17	17
				1244		42		56	28	28
	GS-2	LOW		398	C04	21	C06	38	19	19
		High		381	C04	21	C06	38	19	19
				779		42		76	38	38
				2,023		84		132	66	66

2.3.3 SUMMARY OF SAMPLE ALLOCATION AND CURRENT ENROLLMENT

Table 2-9 summarizes the final distribution of target customers as well as the number of meters that were installed and activated as of October 31, 2003. As seen, overall, enrollment reached 99 percent of target. If the aborted Track A, CPP-V customers are excluded, the enrollment of 2,490 customers actually exceeded the target of 2,328 by almost 7 percent.

Of the 2,490 enrolled, 1,776 are Track A customers, 233 Track B and 481 Track C. There are 602 residential control customers and 261 C&I control customers, or roughly 24 and 10 percent of the overall sample, respectively. The number of residential treatment customers equals 1,374, or roughly 55 percent of the sample, and the number of C&I treatment customers equal 243.

Table 2-9
Revised Target Populations And Enrollment
As of October 31, 2003[33]

		(1)	(2)	(3)	(4)	(5)
Cell ID	**Cell Description**	**Target Enrollment**	**Meters Installed**	**% of Target** Col (2) / Col (1)	**Meters Activated**[6]	**% of Target** Col (4) / Col (1)
A01	Track A, Control, Climate Zone 1	63	67	106%	63	100%
A02	Track A, Control, Climate Zone 2	100	106	106%	103	103%
A03	Track A, Control, Climate Zone 3	100	103	103%	102	102%
A04	Track A, Control, Climate Zone 4	100	103	103%	107	107%
A05	Track A, CPP-F, Climate Zone 1	52	61	117%	63	121%
A06	Track A, CPP-F, Climate Zone 2	188	217	115%	218	116%
A07	Track A, CPP-F, Climate Zone 3	188	226	120%	227	121%
A08	Track A, CPP-F, Climate Zone 4	114	130	114%	134	118%
A09	Track A, CPP-V, Climate Zone 2	62	22	N/A	22	N/A
A10	Track A, CPP-V, Climate Zone 3	63	20	N/A	20	N/A
A11	Track A, CPP-F Info Only, Zone 2	63	69	110%	68	108%
A12	Track A, CPP-F Info Only, Zone 3	63	69	110%	69	110%
A13	Track A, TOU, Climate Zone 1	50	58	116%	58	116%
A14	Track A, TOU, Climate Zone 2	50	57	114%	56	112%
A15	Track A, TOU, Climate Zone 3	50	58	116%	58	116%
A16	Track A, TOU, Climate Zone 4	50	56	112%	57	114%
A17	Track A, C&I <20kW, Control (TOU)	44	44	100%	44	100%
A18	Track A, C&I >20kW, Control (TOU)	44	45	102%	45	102%
A19	Track A, C&I <20kW, CPP-V	58	14	N/A	14	N/A
A20	Track A, C&I >20kW, CPP-V	80	28	N/A	28	N/A
A21	Track A, C&I <20kW, TOU	50	55	110%	55	110%
A22	Track A, C&I >20kW, TOU	50	55	110%	54	108%
A23	CPP-V Control (>600kWh), CZ 2	26	26	100%	26	100%
A24	CPP-V Control (>600kWh), CZ 3	18	18	100%	18	100%
A25	CPP-V Control #2, Climate Zone 2	36	36	100%	36	100%
A26	CPP-V Control #2, Climate Zone 3	27	27	100%	27	100%
A27	Track A, C&I <20kW, Control (CPP-V)	44	44	100%	44	100%
A28	Track A, C&I >20kW, Control (CPP-V)	44	44	100%	44	100%
B01	Track B, Info Only, HunterPt	63	56	89%	48	76%
B02	Track B, CPP-F, HunterPt	126	115	91%	106	84%
B03	Track B, CPP-F, Richmond	64	81	127%	79	123%
C01	Track C, Control	20	20	100%	20	100%
C02	Track C, CPP-V	125	134	107%	133	106%
C03	Track C, C&I <20kW, Control	42	42	100%	42	100%
C04	Track C, C&I >20kW, Control	42	42	100%	42	100%
C05	Track C, C&I <20kW, CPP-V	56	63	113%	59	105%
C06	Track C, C&I >20kW, CPP-V	76	86	113%	85	112%
C07	Track C, Control	100	100	100%	100	100%
Total		2591	2597	100%	2574	99%

33 This table is taken from the October 15th monthly report that was filed by the Utilities with the CPUC.

2.4 CUSTOMER ENROLLMENT

Customers to be enrolled in the SPP were selected through a stratified sample design. A primary customer was randomly drawn from each of the strata that were described earlier. Nine alternative customers, intended to be statistical clones, were also identified. In the original SPP design, customers were to be selected and only allowed to opt-out in the case of significant hardship. However, this was unacceptable to some members of WG 3 appointed by the CPUC to oversee the experiment. A modified design was proposed where customers would be placed on one of the rates and would remain on that rate unless they decided to leave but even that proved difficult for some WG3 participants to accept. The final SPP design involved mailing an enrollment package to selected customers and obtaining an affirmative response regarding the willingness of each customer to participant. As such, it is a voluntary program but one predicated on an opt-out recruitment strategy rather than an opt-in one.

2.4.1 RECRUITMENT

The enrollment package informed customers that they had been selected to participate in an important statewide research project that would test new electricity pricing plans.[34] The enrollment package indicated that participants would be given an appreciation payment totaling $175 ($500 for C&I customers above 20 kW demand) in three installments spanning a period of 12 months. The first installment of $25 was tied to the completion of a survey.[35] The second installment, equal to $75 for residential customers, was paid to all customers that stayed on the rate through the end of the summer and the third installment will be paid to all customers who remain on the experimental rate through April 2004.

In the enrollment package, customers were asked to mail in a reply card or call to affirm their willingness to participate in the experiment. If a customer did not call the toll-free number or mail in the reply card, a recruitment consultant retained by the Utilities made three attempts to call the customer to affirm their participation in the pilot. In some cases, the consultant did not have a working phone number on the customer and sent out a reminder card via mail. If a customer could not be reached after a 14-day deadline passed, they were dropped from the experiment and the recruitment process moved on to one of the nine statistical clones.

Customer recruitment activities were initiated on April 8th and continued through October 17th. For Track A, TOU and CPP-F residential customers, enrollment packages were mailed on April 8th and 9th. Recruitment of Track A, CPP-V customers began on May 13th Track B packages were mailed on June 19th and Track C packages on May 3rd (C&I CPP-V) and May 13th (residential CPP-V). Very low enrollment rates were

[34] An example of an enrollment package is contained in Appendix 3. The packages differed somewhat depending upon the treatment for which customers were being recruited.

[35] The survey is discussed at length in Section 3.

encountered for Track A CPP-V and active recruitment efforts were halted for this track in mid June.[36]

As the experiment progressed, it became clear that the target enrollment numbers would not be reached by the July 1 start date. A number of modifications were made to speed up the enrollment process, while preserving its statistical integrity. These included: (a) raising the number of phone calls, (b) reducing the 10-day deadline for customers to respond, (c) raising the number of statistical clones beyond the original nine and (d) mailing the enrollment package simultaneously to several clones. As a result, the enrollment process became more complex in August. Multiple customers were enrolled for some slots while other slots were not filled. Customers were subsequently reallocated from slots with multiple enrollments to under-enrolled slots for which they were a suitable match.

As of October 31, 8,679 enrollment packages had been mailed out to recruit a target of 1,741 treatment customers (control customers were not recruited, they simply had their meters replaced). This mailing resulted in enrollment of 1,759 customers. A total of 1,332 customers elected not to participate in the experiment and it proved difficult to contact or install meters on 5,134. The vast majority of these were situations where repeated attempts to contact the customer elicited no response. A total of 63 customers, or four percent, elected to opt-out of the experiment between July 1 and October 31, 2003. Details by treatment are provided in monthly reports to the California Public Utilities Commission. Customers who were enrolled in time were placed on their new rates on July 1st. Customers recruited after July 1st were placed on the rate on their next meter read date following installation of the IDR meter.

2.4.2 PARTICIPANT EDUCATION

Once enrolled, customers in various treatment cells were provided with a "welcome package" containing information on how to benefit from the new rate structures. They were also provided a shadow bill, as discussed earlier. Welcome packages varied by rate type and utility. Chart 11 in each package provided information about rates that the typical customer in each treatment cell would be expected to face during the pilot. A copy of one of the welcome packages appears in Appendix 4.

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[36] An analysis of some of the problems associated with the Track A, CPP-V enrollment process is contained in a separate report, Statewide Pricing Pilot—Enrollment Refusal Follow-Up Research, Focus Pointe, October 2003.

3. Data Development

3.1 INTRODUCTION

This section summarizes the data development and impact estimation methodology that underlies the impact estimates and demand models discussed in sections 4 and 5. The residential data are discussed in section 3.2 while the C&I data are summarized in section 3.3.

3.2 RESIDENTIAL DATABASE SUMMARY

The residential impact analysis and demand modeling rely on a variety of data from the following broad categories:

- Energy consumption and peak demand
- CPP event information
- Survey information on appliance holdings and socio-demographic information
- Weather
- Price
- Miscellaneous information (e.g., sample characteristics, etc.).

The specific data used from each of these broad categories is described in the remainder of this subsection. In most instances, data for each customer was provided by the utility that serves that customer. Customer-specific data from multiple databases was linked using an intelligent customer ID. Table 3-1 summarizes the content of the customer ID.

Based on the nomenclature in Table 3-1, the ID A06ESL10303, for example, represents a customer from cell A06 (the CPP-F treatment in climate zone 2) located in SCE's service territory (E), in a single family dwelling (S), who has low usage (L), on the high summer rate treatment (1), who was enrolled as the second alternate for slot 03.

Table 3-1 Intelligent Customer ID Nomenclature		
Character	**Name**	**Definition**
1,2,3	Cell ID	Identifies SPP Track (A, B, C), Sample (CPP-F, CPP-V, control, info only), and Climate zone. Cell values range from A01 to C06
4	IOU	Defines each IOU (E=SCE, P=PG&E, S=SDG&E)
5	Dwelling Type	Dwelling Type for residential samples. S=Single Family, M=Multiple Family, A=All.
6	Usage Level	H=High, L=Low, A=All
7	Rate	Treatment Rate: 1= high summer rate, 2= low summer rate, 0= control
8,9	Slot	Slot Number in the sampling scheme, sequential from 01 to 99
10,11	Alternate	Alternate number in the sampling scheme, 1= for primary sampled account, 2= alternate # 1, 3=alternate # 2,….,10=alternate # 9 11= Replacement, alternates when additional samples were needed. 81- for the cases we recruited new occupants. If we need to do the same for a new occupant at the same site, we will use 82 and so on. 12= substitutes from another cell (for SCE) 99= Substitutes from another cell (for PG&E)

3.2.1 Load Data

The primary load data provided by each utility for customers located in their service territory consists of 96 values for each day representing integrated demand at 15-minute intervals. For purposes of the analysis, the interval data provided by each utility was aggregated to energy consumption by rate period by summing over the corresponding 15-minute intervals. Off-peak period energy consumption for all weekdays covers the time period from midnight until 2 pm and from 7 pm until midnight. Peak-period energy use on all weekdays covers the period from 2 pm to 7 pm for CPP-F customers. For CPP-V customers, the length of the CPP event was either the five-hours from 2 pm to 7 pm or a two-hour period that occurred sometime between 2 pm and 7 pm. If only two hours in length, the time corresponding to the critical period varied from day to day. When the peak period was less than five hours, a CPP-V customer would actually have three rate periods for that day: (1) the two-hour period that is charged at the critical peak rate; (2) the remaining three hours within the eligible peak period that are charged at the normal peak rate; and (3) the remaining hours in the day that are charged at the off-peak rate. Energy consumption during the critical and peak periods was calculated for each CPP-V customer based on the event information described in section 3.2.2.

Diagnostics that were run on the initial load database (e.g., the one covering the pretreatment period and the month of July) indicated that only about 1 percent of the 15-minute interval data provided by the utilities was missing or had zero values.[37] Furthermore, there did not appear to be any systematic pattern or bias in the distribution of missing values across the sample. Consequently, when aggregating the interval data to produce energy use by rate period, missing values were treated as zero and zero values were added in as if they were legitimate unless all of the values in a time period were missing or zero, in which case the aggregate observation was dropped for that day.

3.2.1 Event Data

Event data links CPP events to CPP treatment customers. Specifically, event data indicates whether or not a CPP-F or CPP-V customer will be billed at critical peak rates for a CPP event. A customer is not billed at the CPP rate if the auto-dialer that is used to make the call to customers registers a code called ST, which means “signal in transit.” This indicates that a call was made but could not be completed. For each utility, on average, between two and three percent of customers were not billed for a CPP event. For CPP-V customers, event data is also used to determine the length of the CPP period. This information was used to construct the peak-period consumption values for each customer on CPP-V days.

3.2.2 Survey Data

Data on household characteristics was gathered through a mail survey conducted among both treatment and control customers. Given the essential nature of the survey information to the impact and demand analysis, every effort was made to maximize survey response. Multiple mailings and telephone follow-up calls were made and respondents were paid $25 for completing the survey. Toward the end of the data collection process, in some cases, site visits were made to collect information on non-respondents.

Table 3-2 summarizes the response rate by cell.[38] The overall survey response rate of 90 percent was extremely high. In general, treatment customers responded at a higher

37 A zero value could be a legitimate read since the meters do not record usage of less than 8 watts.

38 Response rate in this instance is defined as the percent of customers for whom load data exists that responded to the survey. This is different from the actual response rate to the survey. For various reasons, (e.g., delays in meter installations; timing differences between when surveys were mailed and when customers enrolled into or left the treatment group, etc.) surveys were sent to some customers who, it was later determined, did not actually participate in the SPP either as a control or treatment

rate than control customers. The response rates for the CPP-F, TOU and Information Only treatment groups were 96, 95 and 96 percent, respectively, whereas the average response rate for the corresponding control group (cells A01 through A05) was 84 percent. The response rate for the CPP-V control groups (C01 and C07) was also 84 percent while the CPP-V treatment group (C02) response rate was 100 percent.

Table 3-2
Load Data and Survey Response By Cell

CELLID	Cell Description	In Load Dataset	In Survey Data	n Both Load and Survey Data	
		Count	Count	Count	Percent of Customers in Load
A01	Track A, Control, Climate Zone 1	68	55	53	77.9%
A02	Track A, Control, Climate Zone 2	105	97	89	84.8%
A03	Track A, Control, Climate Zone 3	105	98	92	87.6%
A04	Track A, Control, Climate Zone 4	106	89	88	83.0%
A05	Track A, CPP-F, Climate Zone 1	60	63	59	98.3%
A06	Track A, CPP-F, Climate Zone 2	209	216	201	96.2%
A07	Track A, CPP-F, Climate Zone 3	216	218	204	94.4%
A08	Track A, CPP-F, Climate Zone 4	132	129	126	95.5%
A09	Track A, CPP-V, Climate Zone 2	17	21	17	100.0%
A10	Track A, CPP-V, Climate Zone 3	18	21	16	88.9%
A11	Track A, CPP-F Info Only, Zone 2	70	66	66	94.3%
A12	Track A, CPP-F Info Only, Zone 3	68	68	66	97.1%
A13	Track A, TOU, Climate Zone 1	57	57	56	98.2%
A14	Track A, TOU, Climate Zone 2	58	51	51	87.9%
A15	Track A, TOU, Climate Zone 3	58	58	56	96.6%
A16	Track A, TOU, Climate Zone 4	55	55	54	98.2%
A23	CPP-V Control (>600kWh), CZ 2	26	31	20	76.9%
A24	CPP-V Control (>600kWh), CZ 3	18	19	14	77.8%
A25	CPP-V Control #2, Climate Zone 2	35	36	27	77.1%
A26	CPP-V Control #2, Climate Zone 3	26	31	21	80.8%
B01	Track B, CPP-F InfoOnly, HunterPt	70	59	51	72.9%
B02	Track B, CPP-F, HunterPt	139	141	117	84.2%
B03	Track B, CPP-F, Richmond	80	73	73	91.3%
C01	Track C, Control	20	28	18	90.0%
C02	Track C, CPP-V	107	153	107	100.0%
C07	Track C, Control	96	83	79	82.3%
Total	Total	2019	2016	1821	90.2%

customer. Indeed, there are 180 customers, or just under 10 percent of survey respondents, for whom there is survey data but no load data. The problem is most apparent in cell C02 where additional customers were surveyed who did not complete the enrollment installation and activation process.

3 Data Development

The customer characteristics survey gathered a variety of information, including data on:

- Appliance holdings
- Appliance usage patterns
- Housing type, age, size and tenure
- Socio-demographic information (e.g., persons per household, education level, language spoken and income)
- Satisfaction with utility performance
- Opinions about the environment.

Table 3-3 contains mean values for selected survey variables, weighted to represent the control group population as a whole. A copy of the survey questionnaire is contained in Appendix 5. The survey vendor recorded the response to each question option as a binary variable. The survey data was typically recoded in order to produce variables that could be used in the analysis. Appendix 6 contains the coding instructions that were used to convert the survey data into regression variables.

Table 3-3
Selected Characteristics of Control Group Customers

Variable	Zone 1	Zone 2	Zone 3	Zone4	State
Persons per Household	3.21	2.98	3.35	3.56	3.18
# of Bedrooms	2.76	2.96	3.04	2.78	2.94
Central air conditioning	0.06	0.29	0.67	0.72	0.42
Income	78,653	71,042	66,294	48,805	68,251
Electric clothes dryer	0.33	0.39	0.30	0.41	0.36
Electric cook top	0.34	0.38	0.35	0.37	0.36
Electric spa	0.01	0.08	0.06	0.05	0.06
Electric water heater	0.09	0.07	0.14	0.08	0.09
Home business	0.04	0.02	0.04	0.03	0.03
Own home	0.71	0.65	0.67	0.65	0.67
College Education	0.56	0.45	0.43	0.21	0.43
Satisfied with Utility	2.95	3.01	2.95	2.92	2.98
Single family dwelling	0.65	0.64	0.71	0.78	0.68
Square footage	1,542	1,526	1,584	1,443	1,537
Swimming pool	0.01	0.07	0.08	0.16	0.08
Home computer use	0.62	0.51	0.60	0.36	0.53
# of freezers	0.16	0.16	0.27	0.31	0.21
# of dishwashers	0.66	0.59	0.66	0.56	0.62
# of households with room a/c	0.03	0.19	0.17	0.19	0.16
# of water pumps	0.02	0.11	0.03	0.11	0.08
# of water beds	0.00	0.00	0.03	0.02	0.01

3.2.3 WEATHER DATA

Weather is an important determinant of energy use and a key explanatory variable in the regression models. Consequently, each control and treatment customer in the experiment was assigned by the relevant utility to a specific weather station located in close proximity to the customer, and weather data was gathered for that station. Data from 58 weather stations was used in the analysis. Table 3-4 lists the weather stations that were used and the corresponding customer population associated with each station. The population values were used to calculate climate-zone-specific, weighted averages for the weather variables. When a weather station was included in more than one climate zone, the distribution of control group customers in the experiment assigned to that weather station was used to allocate the station population to each climate zone.

Table 3-4
Population By Weather Station Used To Calculate Cooling Degree Hour Averages By Climate Zone

Utility	Station ID	Weather Area	Population	Zone 1	Zone 2	Zone 3	Zone 4
PG&E	P05	Concord	236,416		X	X	
PG&E	P06	Oakland	280,055	X	X		
PG&E	P07	San Ramon	81,199		X		
PG&E	P08	Colma	94,604	X	X		
PG&E	P09	Potrero	295,343	X			
PG&E	P10	Ukiah	44,668	X	X		
PG&E	P11	San Rafael	186,424	X	X		
PG&E	P12	Santa Rosa	161,644	X	X		
PG&E	P13	Sacramento	162,848			X	
PG&E	P14	Belmont	144,699	X	X		
PG&E	P15	Milpitas	491,164		X		
PG&E	P16	Santa Cruz	82,392	X			
PG&E	P17	Chico	84,998	X	X	X	X
PG&E	P18	Marysville	50,534		X	X	
PG&E	P19	Red Bluff	48,078	X			X
PG&E	P20	Auburn	124,617	X	X	X	
PG&E	P21	Angels Camp	65,661	X	X	X	X
PG&E	P22	Stockton	235,473			X	X
PG&E	P23	Paso Robles	31,116		X		
PG&E	P24	Salinas	114,703	X	X		
PG&E	P25	Santa Maria	107,566	X	X		
PG&E	P26	Eureka	57,284	X	X		
PG&E	P27	Bakersfield	159,010				X
PG&E	P28	Fresno	327,599	X			X
PG&E	P29	Cupertino	210,199	X	X		
SCE	E01	Tulare	124,357		X	X	
SCE	E02	Mammoth Lakes	10,797		X		

Table 3-4 Population By Weather Station Used To Calculate Cooling Degree Hour Averages By Climate Zone							
Utility	Station ID	Weather Area	Population	Zone 1	Zone 2	Zone 3	Zone 4
SCE	E03	San Dimas	211,541			X	
SCE	E04	Monterey Park	415,914		X	X	
SCE	E05	Ventura	115,460		X	X	
SCE	E06	Romoland	292,609			X	
SCE	E07	Rialto	353,505			X	
SCE	E08	Moorpark	141,237		X	X	
SCE	E09	Rimforest	44,072		X		X
SCE	E10	Valencia	77,528		X	X	
SCE	E12	Bishop	14,271		X		
SCE	E13	Goleta	66,229		X		
SCE	E14	El Segundo	206,231		X	X	
SCE	E15	Long Beach	321,292		X		
SCE	E16	Westminster	244,534		X		
SCE	E17	Santa Ana	713,691		X	X	
SCE	E18	Cathedral Cit	91,506				X
SCE	E19	Blythe	7,965				X
SCE	E20	Ridgecrest	25,362				X
SCE	E21	Barstow	14,645				X
SCE	E22	Lancaster	90,922				X
SCE	E23	Victorville	80,287				X
SCE	E24	Yucca Valley	23,239				X
SDG&E	S01	Lindbergh Field	254,600		X		
SDG&E	S02	Miramar	190,376		X	X	
SDG&E	S03	Montgomery Field	160,157		X	X	
SDG&E	S04	Oceanside Airport	74,951		X		
SDG&E	S05	Gillespie Field	162,609			X	
SDG&E	S06	Brown Field	40,693			X	
SDG&E	S07	Campo	2,930			X	
SDG&E	S08	Ramona	73,202		X	X	
SDG&E	S09	Carlsbad	123,367		X		

Each utility provided temperature and humidity data for each weather station. PG&E and SCE provided average temperature data for each hour of each day, whereas the temperature data from SDG&E was the instantaneous reading at the top of each hour. Previous work by a PG&E meteorologist[39] showed that there is very little difference between average hourly values and peak values within an hour, so the instantaneous readings from SDG&E were treated as if they were the same as the average values provided by PG&E and SCE. Each utility also provided data on relative humidity but this data has not been used to date.

39 Email from Ray Wong, PG&E to Steve George dated 8/13/03 received at 12:47 pm.

The temperature data were used to calculate cooling degree hours by time period. The number of cooling degree hours in an hour equals the difference between a base value, say 72 degrees, and the average temperature in the hour. For example, if the average hourly temperature equals 80 degrees, the number of cooling degree hours in that hour would equal 8. The number of cooling degree hours over a period of time, say the peak period, equals the sum of the hourly values for that period. Thus, if the hourly temperature values during the 2 pm to 7 pm peak period in a day equaled 80, 82, 84, 82 and 78 degrees, the number of cooling degree hours to base 72 in that period would equal 46. A base of 72 degrees was used in the analysis after testing degree hour values to a variety of bases including 68, 70, 72, 74 and 76 degrees. There was very little difference in the results regardless of which base value was used.

3.2.4 Price Data

The estimation of demand models requires development of price data. Given the complexity of electricity tariffs in California, a key issue in the estimation of demand models is how best to represent the price of electricity. There is an extensive literature on this subject dating back to the mid-1970s, and it shows that many different price terms have been used by various analysts, including current and lagged marginal price with and without infra-marginal price terms, price indices, current and lagged average price and total bills.[40] Before discussing the different methods for measuring the price of electricity, it is useful to discuss three criteria by which the methods should be evaluated.

The first criterion is that the method be econometrically sound. That is, it should not create estimation problems that would lead to biased, inconsistent or inefficient estimates of the regression coefficients and ultimately impair estimation of the price elasticities of demand. A problem that is commonly encountered in demand models is simultaneity between price and usage. This occurs if the underlying rate design is either declining block or inverted block. In the SPP case, the rate design is inverted block. The more electricity a customer uses in a time period, the higher the price the customer pays. Thus, if a simple average price, derived by dividing the monthly bill by monthly usage, was used as the price term in the demand model, not only would usage depend on price, but the magnitude of price would depend on the customer's usage. This simultaneous determination of both price and quantity can cause biased estimates of the coefficient on the price term.

A variety of methods can be used to address this problem, including two-stage least squares (2SLS) estimation procedures or indirect least squares (ILS) requiring the use of instrumental variables. A second option is to use lagged price terms (e.g., average price

[40] The "infra-marginal price" is the amount paid by customers on a multi-part tariff for the electricity used up to the marginal block in which they are consuming. In the simplest case of a two-part tariff with a fixed and variable component, the infra-marginal price would equal the monthly fee. However, if the tariff has two tiers in addition to a fixed monthly charge, and the consumer's usage placed him or her on the second tier, the infra-marginal price would equal the fixed charge plus the marginal price of first-tier usage times the length of the tier.

from the previous billing period), but this can lead to loss of data.[41] A third option for reducing, although not completely eliminating, the simultaneity problem is to use the marginal price corresponding to the final tier that the customer is in.[42]

The second criterion is that the price term should bear some relationship to what most customers actually perceive to be the price of electricity. Focus group research conducted as part of the SPP has indicated that, while California customers have a general idea of what they are paying for electricity and understand the concept of time-varying rates, they are not aware of the actual prices (expressed in cents/kWh) they pay. It is important to strike a reasonable balance between accuracy in the price calculation and the likely perceptions that customers have about the prices they are charged. That is, it may be a mistake to use precisely accurate prices if they have little to do with what customers actually perceive.

The third criterion is that the method be computationally parsimonious. Computationally intensive methods can be error prone, time consuming, opaque and expensive without yielding any obvious payoffs in improved parameter estimates.

Within the context of the SPP, there are a variety of methods that could be used to measure price, including the following:

- One approach is to use the prices that were communicated to customers in the Welcome Package they received after enrolling in the SPP. Prices using this approach would vary by rate type (e.g., CPP-F), rate level (high or low) and utility. These prices appear on Chart 11 of the Welcome Package and generally correspond to the average price faced by the average customer. For example, for the CPP-F rate in the SDG&E territory, the current average rate was stated to be 15.5 cents/kWh. The SPP treatment rate was stated to be 10.8 cents/kWh off-peak for 85% of the hours in the year, 27.6 cents/kWh on-peak for 14% of the hours of the year and 76.8 cents/kwh super peak for 1% of the hours of the year. The chart also indicated the specific times for the peak and off-peak periods. This approach is by far the easiest to implement.

- A second approach would begin with development of a composite tariff schedule by climate zone equal to a population-weighted average of the tariffs that exist within each climate zone and service territory. Next, each customer's average daily usage (ADUs) from the previous summer would be used to assign customers to specific tiers within each zone. Finally, average or marginal prices would be computed for the super-peak, peak, and off-peak periods based on the midpoint of each tier by utility, rate type, rate level and climate zone. This assignment of prices would stay constant for an entire season. With this method,

41 In the current instance, we would need to eliminate all of the July data from the demand models so that we could use it to calculate lagged prices.

42 The marginal price varies with usage only when customers move across tiers. For any usage within a tier, the marginal price is constant. The average price, on the other hand, changes with each additional kWh usage even within a tier.

there is some variation in average prices across customers within a season due to the assignment of customers to different tiers based on their historical usage but the simultaneity should be less than with other options because the energy consumption used to calculate prices is fixed, based on historical (e.g., year-old) values.

- A third method is similar to the second except that it allows prices to vary with changes in energy consumption by calendar month. With this approach, average or marginal prices would be determined by assigning each customer to a tier based on usage in the current calendar month. The price for all customers assigned to a tier would be the same and equal to the average price based on usage equal to the mid-point of the assigned tier. For example, if a tier ran from 400 kWh to 700 kWh, and the customers usage in July equaled 600 kWh, the average price for this customer, and for all customers whose usage fell in that tier, would be based on assumed usage of 550 kWh (e.g., the midpoint of the tier).

- A fourth method would take each customer's usage by calendar month and compute their actual, customer-specific prices rather than using the mid-point of the tier (i.e., each customer's usage would be run through the bill calculator that was developed at the beginning of the project to establish the SPP rate designs). If marginal prices were used in the two methods rather than average prices, this method and the previous one would result in the same values. However, with average prices, the result would be different. The advantage of this approach over the following one is that it avoids the need to grapple with billing cycle issues. Dealing with billing cycles as opposed to calendar months is much more complex computationally and also introduces additional econometric issues.

- A final option would use the average price paid by customers based on their actual billing cycle energy consumption, lagged one period. It should be noted that this option would result in the exclusion of the July data from the regression analysis, as the approach only makes sense under the assumption that customers base their usage decisions in a billing cycle on the price information received in the previous bill.

After evaluating the options described above, an initial decision was made to pursue option 3. This option appeared to strike a reasonable compromise between accuracy, computational ease and minimization of econometric problems. Unfortunately, option 3 did not fare well in practice. It yielded positive and statistically significant estimates of the price elasticities of demand across all rate types and day types. On further examination, it became clear that the regression results were being dominated by the simultaneity problem described above. The coefficients on the price terms did not represent the negative slope of the demand curve but reflected instead the upward slope of the inverted five-tier rate schedule.

This was confirmed when the data were subdivided into five tiers and separate regression models were estimated for each tier. This "Option 6" yielded reasonable estimates of price elasticities within each tier for most rate types. However, since the sample was not designed to produce meaningful results at the tier level, an alternative approach was pursued.

First, 2SLS was used to estimate the demand models. This involved estimating an "instrumental variable" model in which price is regressed on factors other than usage. Variables used in the first stage included appliance holdings, household socio-demographic characteristics, weather and binary variables representing climate zone, utility and CARE/non-CARE pricing.[43] The predicted value of price obtained from the instrumental variable regression was then used as the price term in the demand function. Unfortunately, the results from this approach were largely unsatisfactory (e.g., statistically insignificant, wrong signs, etc.), confirming that the problem of simultaneity was sufficiently strong that even the 2SLS procedure failed to remove it.

Second, a variant of Option 1 was explored, where prices for all customers were set equal to the average price for a customer with consumption at the midpoint of tier 3. This approach approximates Option 1 except that prices were allowed to vary as general rate adjustments occurred for each utility over the treatment period. The prices also reflect whether or not a customer receives the CARE discount. With this approach, prices primarily reflect the experimental design and do not vary with customer usage, essentially making them ideal instruments for the demand models.

Reasonable results (described below) were obtained using the average price for a customer at the midpoint of tier 3. To test the sensitivity of the results, models were also estimated using the average price for customers at the midpoint of tier 1 and tier 2. The results were quite robust across the three price sets.[44] This is not surprising since the TOU and CPP rates implicitly impose a constant surcharge on the underlying rates during the peak and critical peak period and give a credit during the off-peak period. The amount of the surcharge and credit does not vary by tier. Since customers are spread across all five tiers, and since the average customer in all three utilities is usually a tier 3 customer, a decision was made to use the average price for a tier-3 customer.

Demand models were also estimated using both average and marginal prices. On average, the difference in the estimated elasticities was only 2 percent. A decision was made to use average prices because they correspond more closely to the prices in the Welcome Package. They also are conceptually the same as the prices that customers see in the supplementary billing sheet they receive each month.

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43 Low-income customers are eligible for a 20% discount on their monthly electric bill through a program called CARE, California Alternate Rates for Energy. For details about PG&E's CARE programs, consult http://www.pge.com/care/.

44 Separate demand models were estimated using the average price for a customer at the midpoint of tier 1, tier 2 and tier 3. The results were generally similar, in terms of the overall goodness of fit of the regressions, as measured by the R-square values, and the magnitude and statistical significance of the price elasticities of demand. A decision was made to use Tier 3 prices since the "typical" customer for each utility lies in Tier 3.

In order to calculate average prices for customers in Tier 3, a composite tariff was constructed for each climate zone based on a population-weighted average of the baseline quantities associated with each of the baseline regions within each utility and climate zone. The resulting baseline quantities that were used to calculate average and marginal prices for each utility, climate zone and season are contained in Table 3-6.

Table 3-5
Average Baseline Quantities (kWh)
Used to Calculate Average and Marginal Prices

Utility	Season	Zone 1	Zone 2	Zone 3	Zone 4
PG&E	**Summer**	264	384	485	548
PG&E	**Winter**	312	392	386	375
SCE	**Summer**	n/a	313	472	754
SCE	**Winter**	n/a	305	353	343
SDG&E	**Summer**	n/a	315	313	n/a
SDG&E	**Winter**	n/a	327	347	n/a

Appendix 7 contains the prices that were calculated for use in the demand analysis. An illustrative set of prices from PG&E in Zone 2 are contained in Table 3-5. Both marginal and average prices are presented for zone 2 for each tier, as well as data on the ratio of treatment to control group prices, and the percentage and absolute differences between treatment and control prices. PG&E's prices have remained constant throughout the experimental period. SCE has had two price changes, with the most significant one going into effect on August 1 and the second on September 1. SDG&E has had three minor price changes since July 1, with effective dates of September 1, October 1 and October 7. Appendix 9 presents data for two pricing periods. Period 1 represents the prices that were in effect in early July, when most treatment customers were placed on the experimental rate. Period 2 reflects the August 1 price change for SCE and the September 1 price change for SDG&E (and the original prices for PG&E since PG&E's prices never change).

Table 3-6 CPP-F Illustrative Average Prices (PG&E, Zone 2, Tier 3 Customer)				
Rate Level	**Daily Price (¢/kWh)**	**Critical Peak Price (¢/kWh)**	**Peak Price (¢/kWh)**	**Off Peak Price (¢/kWh)**
High Summer Ratio	12.2	73.8	24.5	7.8
Low Summer Ratio	14.3	54.4	22.4	11.4
High Summer Ratio (CARE)	8.0	57.3	17.9	4.5
Low Summer Ratio (CARE)	9.7	41.8	16.2	7.4

3.2.5 Miscellaneous Data

A variety of miscellaneous data was gathered in order to investigate potential selection bias and/or for possible use in the impact analysis. Each utility provided the following information for every customer that was chosen as part of the recruitment sample:[45]

- Average daily summer usage for the 2002 summer
- Weather station ID
- Housing type
- An indicator of whether or not a customer was contacted as part of the enrollment process
- An indicator of whether or not a contacted customer could be reached after the requisite number of attempts
- An indicator of a meter installation failure for customers that agreed to participate or for control customers
- An indicator that a contacted customer was ineligible due to plans to move within six months (a prerequisite for participation was that the customer was not planning to move within six months)
- An indicator of refusal to participate
- The customer's address.

For CPP-F and CPP-V customers who agreed to participate in the experiment, information was also obtained on their preferred optional notification methods.[46] For

45 Recall from section 2 that multiple "clones" were drawn for each required sample. In the initial sample draw, SCE and SDG&E selected 10 clones for each slot while PG&E selected 20. In a few instances where all slots were not filled even after using the 10 clones, an additional 10 clones were drawn. In total, the sample database contains information on roughly 23,000 customers, of which roughly 15,000 are in PG&E's service territory, 3,800 are in SDG&E's service territory, and 3,400 are in SCE's service territory.

treatment customers participating in the SPP, information was obtained on the number of times per day that each customer accessed their usage information via the experimental web site established for that purpose. This information will eventually be used to determine whether there is any correlation between web access and rate impacts.

3.3 C&I DATABASE SUMMARY

The data development process for the C&I sector was virtually identical to that of the residential sector for energy use and peak demand, CPP event information, weather[47] and miscellaneous experimental data. Consequently, a description of the development process for these databases will not be repeated. Regarding C&I prices, since C&I rates do not involve tiers, the problem of simultaneity encountered in the residential sector is not encountered. Thus, we were able to use average prices for C&I customers. The average values are based on energy use for the typical customer in each segment based on load research data from 2002. The relevant prices for the LT20 and GT20 customer segments for the TOU and CPP-V rates are shown below in Table 3-7.

Table 3-7
Average Prices For C&I Customers During Treatment Period
($/kWh)

Customer Segment	Rate Treatment	Price Ratio	Non-CPP Day		CPP-Day	
			Peak Period	Off-Peak Period	Peak Period	Off-Peak Period
LT20	**Control**	**N/a**	0.186		0.186	
	TOU	**High**	0.272	0.094	0.272	0.094
		Low	0.325	0.159	0.325	0.159
	CPP-V	**High**	0.200	0.095	1.07	0.091
		Low	0.256	0.169	0.813	0.166
GT20	**Control**	**N/a**	0.154		0.154	
	TOU	**High**	0.224	0.100	0.224	0.100
		Low	0.254	0.144	0.254	0.144
	CPP-V	**High**	0.187	0.086	0.820	0.084
		Low	0.212	0.137	0.629	0.136

As with the residential sector, a survey was conducted to obtain customer characteristics information for C&I customers. In the case of C&I customers, the survey was much

46 The primary notification for all customers is via a landline telephone. However, customers were given the option of having additional notification options, including an alternative landline, a cell phone, email and pager.

47 The C&I sample was not segmented by climate zone so there was no need to map weather stations into climate zones for the C&I analysis.

shorter than the residential survey. Appendix 8 contains the survey questionnaire. In brief, the C&I survey gathered the following types of information:

- Size of structure (in square feet)
- Percent of structure that is air conditioned
- Tenure (e.g., own or lease)
- Whether the bill is paid directly or as part of the rent
- Hours of operation
- Thermostat setting
- The presence of an energy management system
- Number of employees
- Type of business.

Table 3-7 shows the completion rates by cell for the C&I survey. As seen, the survey completion rate for C&I customers was even higher than for residential customers, with an overall response rate of 95 percent.

Table 3-8
C&I Survey Completion Rates By Cell ID

CELLID	Cell Description	In Load Dataset	In Survey Data	In Both Load and Survey Data	
		Count	Count	Count	Percent of Customers in Load
A17	Track A, C&I <20kW, Control (TOU)	47	43	43	91%
A18	Track A, C&I >20kW, Control (TOU)	48	45	45	94%
A19	Track A, C&I <20kW, CPP-V	13	12	11	85%
A20	Track A, C&I >20kW, CPP-V	28	31	28	100%
A21	Track A, C&I <20kW, TOU	54	55	53	98%
A22	Track A, C&I >20kW, TOU	53	57	53	100%
A27	Track A, C&I <20kW, Control (CPP-V)	47	45	45	96%
A28	Track A, C&I >20kW, Control (CPP-V)	44	44	44	100%
C03	Track C, C&I <20kW, Control	44	43	43	98%
C04	Track C, C&I >20kW, Control	47	43	43	91%
C05	Track C, C&I <20kW, CPP-V	58	61	54	93%
C06	Track C, C&I >20kW, CPP-V	89	87	80	90%
Total		572	566	542	95%

4. Impact Estimation Methodology

This section provides an overview of the economic theory underlying the demand models that are used to estimate the impact of time-varying rates in the SPP, describes the specific equations that are used to estimate the relationships between electricity demand and price by rate period, discusses econometric issues in model estimation, and addresses the issue of selection bias in the SPP.

4.1 OVERVIEW OF DEMAND SYSTEMS

The impact estimation methodology relies on the specification and estimation of demand systems that explain customer behavior around electricity use. These demand systems are derived from the modern theory of economic behavior, which is briefly summarized in the next sub-section. This is followed by a discussion of various elasticity concepts and mathematical functional forms.

4.1.1 THEORY OF CONSUMER DEMAND

In the modern theory of consumer behavior, the individual is assumed to consume goods and service in order to maximize the "utility" he or she derives from the act of consumption, subject to a budget constraint that the sum of all expenses (including savings) cannot exceed the consumer's income.[48] Conceptually, each consumer faces the following optimization problem:

*Maximize **utility**, which is a function of the quantities consumed of the various goods and services, subject to a **budget constraint**.*

For reasons that are discussed below, the utility function is called the **direct utility function, U**. If U is continuous and twice differentiable, a solution to the consumer's optimization problem can be obtained by using the well-known techniques of the calculus. Otherwise, a solution can be obtained by using the Kuhn-Tucker conditions of mathematical programming. In general, the "first order conditions" of optimization suggest that the consumer should "demand" quantities of each good and service until the ratio of the marginal utilities for goods i and j equal the corresponding price ratios. The "second order condition" of optimization suggests that the underlying U function be concave to the origin, and that the consumer's marginal rate of substitution between goods i and j diminish with increasing j.

Solving this optimization problem yields **demand functions, D,** that express the quantity the consumer will purchase of a particular good, such as electricity, as a function of the

[48] See Deaton, Angus S. and John Muellbauer. *Economics and consumer behavior*. Cambridge University Press, 1980 and Pollak, Robert A. and Terence J. Wales. *Demand system specification and estimation*. Oxford University Press, 1992.

price of electricity, the prices of all other goods and services, and the consumer's income. A University of Cambridge economist, Alfred Marshall, first put forth a graphical way of summarizing the nature of demand functions. Called a demand curve, this shows how the quantity demanded varies with price.[49] Along a Marshallian demand curve, the consumer's income is held constant, along with the prices of all other goods and services. The consumer's utility varies along the Marshallian demand curve. A few decades later, another English economist, Sir John Hicks of Oxford University, put forth a set of demand curves that hold the utility constant along the curve.[50] They are called Hicksian (or compensated) demand curves.

The SPP has collected detailed data on electricity consumption by pricing period, but, like most electricity pricing experiments, it has collected minimal information on non-electricity goods and services. To operationalize the theory laid out above, it is necessary to separate the U function into electricity and non-electricity goods and services. This is a fairly common procedure in empirical work.

The U function is assumed to be separable into two subfunctions, one dealing with electricity (let's call it U1) and the other dealing with non-electricity (U2). U1 can be thought of as being an index of aggregate electricity consumption. Optimization of U1 yields a set of electricity-related demand functions, D1, that relate electricity consumed in the various pricing periods to electricity prices in each of the periods and total expenditures on electricity (rather than consumer income). In addition, recognizing that consumers who differ in socio-demographic characteristics and appliance holdings are likely to use electricity differently, it is common practice to include explanatory variables on the right hand side that measure the sizes of these variables. Finally, since weather conditions have a major impact on electricity consumption, it is useful to include weather variables as explanatory variables.

In empirical work, it is often more convenient to work with the **indirect utility function**, **V**, rather than with the direct utility function, U. The V function is obtained by plugging in the demand functions, **D**, back into the direct utility function, **U**. The **indirect utility function, V,** expresses consumer well being as a function of prices and income. It is possible to derive the Marshallian demand functions from V by using Roy's identity, which says that the demand functions are equal to the ratio of the differential of V with respect to a good's price to the differential of V with respect to income. Just like the U function was separated into electricity (U1) and non-electricity (U2) sub-functions, V can also be separated into electricity (V1) and non-electricity (V2) sub-functions. V1 can be thought as being an aggregate price index of electricity.

Finally, it is appropriate to mention the **expenditure (or cost) function, E.** This function is often used to examine changes in consumer welfare, and it plays a key role in cost-benefit analysis. **E** is obtained by solving the "dual" problem of minimizing the budget, subject to a given direct utility function. Solving this problem yields a set of Hicksian

[49] Marshall, Alfred. *Principles of Economics*. 8th edition, Macmillan & Co. Ltd., 1922.

demand functions that express the quantity consumed as a function of prices and utility. Substituting these demand functions into the budget constraint yields the expenditure function, which expresses demands as a function of prices and utility. According to Shepard's lemma, the Hicksian demand functions can be obtained by differentiating the expenditure function with respect to the prices.

4.1.2 Elasticities of Demand and Substitution

Elasticities relate changes in consumer demand to changes in explanatory variables such as prices and income. In the case of electricity, the most frequently used elasticities are the own price and cross-price elasticities of demand. A related concept is the elasticity of substitution (ES). Another concept is the income elasticity of demand.

The own-price elasticity of demand expresses the percent change in demand that occurs in response to a one percent change in the commodity's price, while the cross-price elasticity of demand relates the change in demand in response to a one-percent change in the price of a related commodity.[51] This definition yields e technically a point elasticitiy of demand, since it deals with small changes at a single point along the demand curve. When the price changes being considered are substantial, say on the order of 100 percent or higher for price increases, it is best to not rely on a point elasticity and instead to compute an "arc elasticity" through model simulation.

Own-price elasticities are always negative, while cross-price elasticities can be positive if two goods are substitutes in consumption or negative if the goods are complements in consumption.

Price elasticities are partial concepts that are calculated with all other variables in the demand function being held constant. They can be calculated for either Marshallian or Hicksian demand functions. In the former case, they are called uncompensated elasticities and in the latter case they are called compensated elasticities.

The elasticity of substitution pertains to the shape of the indifference curves that underlie the U function. It is closely related to the own-price and cross-price elasticities of demand.[52] It was first put forth by R. G. D. Allen, a British economist who taught at the London School of Economics.

The income elasticity of demand expresses the change in demand that occurs in response to a one-percent change in income.

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[50] Hicks, John R. *Value and Capital.* 2nd edition, Oxford University Press, 1946.
[51] For a general discussion of price elasticity and related concepts, consult a basic economics textbook such as Paul A. Samuelson and William D. Nordhaus, *Economics*, Sixteenth Edition, Irwin McGraw-Hill, 1998.
[52] This relationship is discussed further in section 4.4.

When the price of a commodity increases, a consumer will use less of that commodity if nothing else has changed. There are two reasons for this. First, since the commodity has become more expensive relative to its substitutes, the consumer uses less of it. This is a "pure" price effect, and is measured as a movement along the Hicksian demand curve. The reduction of consumption is called the substitution effect, and it can be estimated by using the Hicksian own-price elasticity of demand. The second reason a consumer will reduce consumption of the commodity in question is that his or her income has diminished in purchasing power. As a result, the consumer consumes less of this commodity and all other commodities. This reduction in consumption is called the income effect, and it can be estimated by the income elasticity of demand, weighted with the share of this commodity in the consumer's budget.

A Russian economist, E. E. Slutsky, derived a relationship between these effects in an equation that is named after him. The equation states that the own-price elasticity of demand equals the compensated own-price elasticity of demand plus the product of the income elasticity of demand and the budget share of the commodity in question.

4.1.3 CROSS-EQUATION CONSTRAINTS

Various restrictions on the price and income elasticities of demand flow from the budget constraint, which says that spending on all goods must equal income. According to the Engel constraint, a weighted average of the income elasticities should equal one, where the weights are the budget shares. If some goods are luxuries, with income elasticities of greater than one, others have to be necessities, with income elasticities less than one.

According to the Cournot aggregation, a weighted average of the own-price elasticity for good i with all cross-price elasticities should equal the negative of its budget share, where the weights are the budget shares as before.

Finally, according to the Euler aggregation, the sum of all own-price and cross-price elasticities for good i has to equal the negative of the income elasticity of good i.

As will be seen later when we discuss specific functional forms, these constraints appear as a set of restrictions that apply to the resulting system of demand functions.

4.1.4 ESTIMATING DEMAND SYSTEMS

Having reviewed the key theoretical concepts, we can now lay out a series of steps for estimating demand functions for electricity consumption by time period. The ultimate objective is to determine consumer preferences (or utility) associated with consuming electricity by TOU period. However, since preferences cannot be measured directly, we need to estimate demand functions in order to infer them. In our earlier discussion, we showed that the demand functions were derived by differentiating either the direct utility function (U), the indirect utility function (V) or the expenditure function (E). If the demand functions satisfy what Paul Samuelson has called the integrability conditions, we can infer preferences from them.[53]

So far the discussion has been carried out in general terms. For the system of demand equations to be estimated with real data, it is necessary to specify the mathematical functional form of one of the three functions that measure consumer preference. There is no universally accepted functional form in the economics literature that dominates all other forms, since each functional form has its strengths and weaknesses and all are approximations to an underlying but unknown functional form.

Four functional forms are commonly used in the literature dealing with TOU pricing:

- Double-Logarithmic (DL)
- Quadratic
- Constant-elasticity-of-substitution (CES)
- Generalized Leontief (GL)

4.1.4.1 Double-Logarithmic (DL) Functional Form

Th DL model specification has been used to estimate demand systems for all types of consumer goods and services, largely because of its simplicity of interpretation and ease of estimation. The coefficients on the price terms are the (point) elasticities, and can be directly read off the estimation printouts. In addition, the equations can often be estimated through ordinary least squares (OLS).[54]

The purists regard the double-logarithmic functional form as an ad hoc specification, since its demand equations are not strictly consistent with the economic theory outlined earlier in this section. In other words, they cannot be obtained from the process of utility maximization. They can accommodate the homogeneity restrictions due to Euler (demands should be unchanged if all prices rise by the same amount as income) but not the Engel or Cournot aggregation restrictions discussed earlier.

The natural logarithm of electricity usage is made a function of the natural logarithm of the on-peak and off-peak prices, and all the other variables such as socio-demographic and economic characteristics and weather. This functional form has the advantage of instantly yielding the (point) price elasticities of demand. For example, the coefficient of the peak period price in the equation for peak period usage is the (point) own-price elasticity of demand for on-peak usage, and the coefficient of the (point) off-peak price in the same equation is the cross-price elasticity between on-peak usage and off-peak price.

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[53] Samuelson, Paul A. *Foundations of Economic Analysis*. Harvard University Press, 1947.

[54] For a discussion of OLS and other means of performing regression analysis, consult a text such as Johnston, Jack and John DiNardo. *Econometric Methods*. Mc-Graw Hill, 1997.

Consequently, all own-price and cross-price elasticities are constant across various price levels. Some analysts find this fact disconcerting, citing anecdotal evidence that price elasticities vary with the level of price. At very low prices, customers do not respond to price changes. At very high levels, they have exhausted their ability to respond. Most of the "average" response occurs at moderate price levels. The DL functional form can be modified to capture such non-linearities in customer response to price changes. The easiest way to accomplish this is to introduce cross-product variables on the right hand side, consisting of the product of the various price terms and the socio-demographic, economic and weather terms.

4.1.4.2 Quadratic Functional Form

Like the DL functional form, the quadratic functional form is not derived from the theory of utility maximization. However, it is widely used in the empirical literature, since it overcomes one of the weaknesses of the DL functional form, which is the constancy of the estimated price elasticities. On-peak period usage is expressed as a linear combination of the on-peak and off-peak prices, of the squares of these prices, and of all the non-price terms mentioned above. The price elasticities are not constant in this functional form, but vary with price. If the coefficients on the squared terms are zero, or statistically indistinguishable from zero, this functional form reduces to a linear demand system.

4.1.4.3 Constant-Elasticity-of-Substitution (CES) Functional Form

The CES functional form was developed jointly in 1961 by four economists, Kenneth Arrow, Hollis Chenery, Bagicha Minhas, and Robert Solow. Arrow and Solow were subsequently awarded the Nobel Prize, partly for their research on the CES functional form. The CES has been widely used in the empirical literature, on both the producer and consumer fronts.

For the two-part TOU rate, this functional form expresses the ratio of peak and off-peak usage as a function of an intercept term, the ratio of peak and off-peak prices and all the non-price terms mentioned above. The coefficient on the price ratio is the elasticity of substitution, which is related to the own-price and cross-price elasticities of demand, as shown in section 4.4. The intercept term is the ratio of peak and off-peak usage in the control group.

This functional form has been widely used in the analysis of TOU experiments.[55] For example, it was used in the analysis of the Southern California Edison and Wisconsin experiments, and in EPRI's analysis of the top five pricing experiments (Connecticut, Los Angeles, North Carolina, Southern California, and Wisconsin). The CES function has

[55] Aigner, Dennis (editor). Welfare econometrics of peak-load pricing of electricity. *Journal of Econometrics*, *Annals* 1984-3. North-Holland, 1984.

the advantage of being fully consistent with the neoclassical theory of utility maximization discussed earlier. It is valid for any non-negative value of the elasticity of substitution, and it satisfies globally the second-order (concavity) conditions associated with utility maximization.

It includes as a special case two popular functional forms, the Cobb-Douglas functional form, which features a constant ES of one, and the Leontief functional form, which features an ES of zero. The Leontief functional form, due to Nobel laureate Wassily Leontief, is also called the fixed-coefficients functional form, since it asserts that consumers use products in a fixed proportion to each other and there is therefore no potential for substituting one for the other when their relative prices change.

Researchers have used both functional forms on a stand-alone basis for estimating consumer demand systems for a variety of products such as food, clothing and housing. However, since prior electricity pricing experiments have shown that consumers do respond to TOU pricing in a statistically significant but small fashion, the Cobb-Douglas form has not been used for estimating response to TOU pricing.

4.1.4.4 Generalized Leontief (GL) functional form

The GL functional form, due to Erwin Diewert, is a generalization of Leontief's fixed-coefficient functional form discussed above.

The direct utility function expresses customer satisfaction (utility) as a function of the square root of the quantities consumed. The associated demand functions express the logarithms of the quantity ratios as functions of the logarithms of the ratios of the square root of prices.

Like the CES function, the GL function is consistent with the neoclassical theory of utility maximization. It does not constrain the ES to be constant, and is therefore called a "flexible" functional form. However, this flexibility comes at a price. Unlike the CES, the GL is not valid for all possible values of the true ES . It is well suited to modeling demand systems with "small" price elasticities, such as those found in most TOU studies.[56]

4.1.5 IDENTIFYING THE SPECIFIC VARIABLES TO BE INCLUDED IN THE ANALYSIS

The primary variables of interest to us in the SPP are the quantities of electricity (kWh) consumed by time-of-use (TOU) period. Ideally, the system of demand equations would express the quantity demanded of electricity by TOU period as a function of the price of electricity in the various pricing periods, the prices of all other goods and services, and

[56] Another flexible functional form, the Translog, is well suited to modeling demand systems with "large" price elasticities. This functional form was used by a variety of researchers in a variety of TOU pricing experiments, and found to be unstable, since the underlying price elasticities are small.

consumer income. Unfortunately, in most electricity pricing experiments, we only have data on electricity prices and consumer expenditure on electricity. Data is generally not available on the prices of other goods and services, or on consumer income. Such is also the case with the SPP.

Thus, we cannot deal with the utility maximization problem in its entirety. We are forced to decompose the consumer's optimization process into two stages. In the first stage, the consumer decides how much electricity to consume, as a function of the price of electricity and the prices of all other goods and services, for a given level of income. This stage cannot be observed in the experiment, but we know it does exist in reality. In the second stage, the total amount of electricity is allocated to the various pricing periods. This stage is observable in the experiment. The demand functions will relate the quantity of electricity consumed by TOU period to the electricity prices during the various periods and total electricity expenditures.

We can further refine the specification by accounting for other variables that explain the variation in electricity use, over time and across customers. For example, it is reasonable to expect that consumption will vary across households that differ with respect to socio-demographic and economic characteristics. These variables include the number of people in the household, the age of the head of household, the size of the dwelling (square feet), the type of dwelling (single family detached, multi-family, or mobile home), ownership of the dwelling, the holdings of major electrical appliances, and the income of the household. These variables are normally included as explanatory variables on the right hand side of the demand equations. Socio-demographic and economic information on customers is typically collected through surveys that are administered at the beginning (and possibly toward the end) of the experiment.

It is also reasonable to expect that for a given household, consumption would vary from day-to-day and month-to-month based on weather conditions. These variables are normally included as explanatory variables on the right hand side of the demand equations. Weather conditions are typically measured in terms of cooling and heating degree days or degree hours, and such data are often available from weather stations.

4.2 MODEL SPECIFICATION

In this sub-section, we present the specific mathematical equations that are used to specify two of the functional forms discussed in the previous section. These are the CES and double-log functional forms.

4.2.1 CONSTANT-ELASTICITY-OF-SUBSTITUTION (CES)

The CES functional form has been widely used in the literature on demand functions and has been applied by a number of researchers to the analysis of TOU pricing data. We have also estimated the double-logarithmic functional form and found considerable similarity in results between the two specifications. We prefer the CES specification since it has fewer parameters (e.g., two, the elasticity of substitution and the daily price elasticity) compared with the double-log specification (e.g., four own- and cross-price elasticities) and because it is derived from the modern theory of consumer demand discussed in the previous section. Furthermore, conventional price elasticities of demand for peak and off-peak energy use can be derived from the CES equations as illustrated later in this sub-section.

The CES demand system consists of two equations. The first equation models the ratio of peak to off-peak quantities as a function of the ratio of peak to off-peak prices and other terms. Since the quantity ratio can be uniquely mapped to the shares of peak and off-peak quantities in daily usage, the equation can intuitively be considered a share equation. The second equation yields a prediction of daily electricity use. Thus, by taking the shares of energy use by period that are predicted by the first equation and multiplying them b predictions of daily energy use from the second equation, we generate predictions of the quantity levels for peak and off-peak use. This is discussed later in the section dealing with Model Prediction.

Given the panel nature of the data set, we have used the "fixed effects" estimation procedure to derive the model parameters. This procedure, discussed in the following section on model estimation, assigns a binary variable to each customer that represents the unique and unexplainable lifestyle of each customer. Since the effect is specific to each customer and does not change over time, it is called a fixed effect.

The first CES equation, referred to as the energy-share equation, is specified as follows:

$$[illegible]\ CDHD \qquad (1)$$

where
- Q_p = average energy use per hour in the peak period for the average day
- Q_{op} = average energy use per hour in the off-peak period for the average day
- σ = the elasticity of substitution between peak and off-peak energy use
- P_p = average price during the peak pricing period
- P_{op} = average price during the off-peak pricing period
- δ = measure of weather sensitivity
- CDH_p = cooling degree hours per hour during the peak pricing period[57]
- CDH_{op} = cooling degree hours per hour during the off-peak pricing period
- θ_i = fixed effect for customer i

D_i = a binary variable equal to 1 for the i^{th} customer, 0 otherwise, where there are a total of N customers.

ε = regression error term

The second equation in the CES model estimates daily energy use as a function of daily average price and daily cooling degree hours. The daily model is specified as follows:

$$\ldots CDHD \qquad (2)$$

where Q_d = average daily energy use per hour

η_d = the price elasticity of demand for daily energy

P_d = average daily price (e.g., a usage weighted average of the peak and off-peak prices for the day)

CDH_d = cooling degree hours per hour during the day

ε = regression error term

It is plausible that the elasticity of substitution or the daily price elasticity would differ between customers with and without CAC and also between hot and cool days. To accommodate this probable behavior, it is useful to specify the CES model where the elasticity is a function of weather conditions and CAC. This yields the following demand model:

$$\ldots CDHCDHCDH \qquad (3)$$

The composite elasticity of substation (ES) in this model is a function of three terms, as shown below:

$$ES \ldots f(\ldots CDH\,CAC) \qquad (4)$$

As discussed in Section 5.1.3, other customer characteristics, such as income, household size, etc, may also influence the elasticities in the CES model. They would

[57] The difference in cooling degree hours was used in the CES specification rather than the ratio of cooling degree hours in the two time periods because, in some climate zones, the value for off-peak cooling degree hours equals 0. In these cases, calculating the ratio would involve dividing by zero.

be included in the specification through interaction terms in a similar manner to the CAC and weather terms shown above.

4.2.2 DERIVING OWN AND CROSS-PRICE ELASTICITIES FROM THE CES MODEL SPECIFICATION

Point estimates of the own-price and cross-price elasticities of demand for the CES demand model can be derived as follows.[58] As noted earlier in equation (1), the CES demand model is specified by the following equation (where the weather term, the fixed effects and the other interaction terms have been dropped for simplicity):

Also, when there are only two usage periods, the following identity holds:

$$Q_d = Q_p + Q_{op}$$

where Q_d = average energy use per hour.

Specify the following equation for daily electricity use and price,

$$\ln(Q_d) = \alpha + \eta_d \ln(P_d) \quad (5)$$

where P_d = average daily price (e.g., a usage weighted average of the peak and off-peak prices for the day),

$$P_d = w_p P_p + w_{op} P_{op} \quad (6)$$

where w_p = total peak period electricity use and w_{op} is similarly defined.

To further simplify, we define the following budget shares:

(7)

[58] Arc elasticities have to be derived through model simulation.

$$wP \qquad (8)$$

Combining relevant equations and terms, we get the following expressions for the Marshallian own- and cross-price elasticities of demand:

$$dz \qquad (9)$$

$$dz \qquad (10)$$

$$dz \qquad (11)$$

$$dz \qquad (12)$$

where η_p = own-price elasticity in the peak period

η_{pop} = cross-price elasticity in the peak period

η_{opp} = cross-price elasticity in the off-peak period

η_{op} = own-price elasticity in the peak period.

4.2.3 DOUBLE-LOGARITHMIC (DL)

The double-log specification also requires two equations, one for peak-period energy use and the other for off-peak energy use. Each equation has both peak and off-peak prices included in order to estimate the own- and cross-price elasticities of energy demand for each time period. The two equations are specified as follows:

$$\sum \ldots EDH \qquad (13)$$

$$\sum \ldots EDH \qquad (14)$$

4.2.4 PREDICTING IMPACTS OF DIFFERENT RATES

One of the primary objectives of the SPP is to develop demand models that can be used to predict the impact not only of the rates tested in the SPP but also alternative rate levels. In doing so, it is not appropriate to use point elasticities that are estimated for each model, since they are only accurate for measuring the impact of small price changes. It is essential to use the full demand models when making impact predictions.

This section presents an example of the derivation of the equations that can be used to predict changes in electricity use by time period given a change in time-varying rates. The derivation is done for a three-period tariff (such as the CPP-V rate on CPP days when the control period is less than the full peak period).[59] A three-period rate would include a peak period, an off-peak period and a shoulder period.[60] To keep the algebra simple, the derivation presented here is for a basic demand model that excludes weather impacts on usage and also excludes interaction effects between the elasticity of substitution and saturation of central air conditioning and weather. The SPP Impact Simulator software that is used to predict the impacts of SPP rates presented in Sections 4 and 5 of this report includes the additional terms where appropriate.

In the baseline case with non-time varying prices (which apply to the control group in either the pre-treatment period or the treatment period and the treatment group in the pre-treatment period), the following relationships hold:

[illegible] (15)

and,

[illegible] (16)

where Q_i = energy usage in period i and P_i = price per Unit of energy in period i

The following identity is defined:

$$Q_t = Q_1 + Q_2 + Q_3 \tag{17}$$

59 Following the same approach, one can derive the impact prediction equations for other functional forms, such as the DL, GL and quadratic.

60 As a practical matter, since the SPP only used two time periods (peak and off-peak), only the elasticity of substitution between peak and off-peak usage was estimated. Thus, when applying the formulas noted below, we have to assume that $b_{12} = b_{32}$.

The following relationships hold when time-differentiated prices, denoted by primes, are introduced:

(18)

(19)

and,

(20)

Start by subtracting equation (15) from (18)

(21)

Equation (21) becomes:

(22)

Set the following quantity to A:

(23)

Thus, equation (22) becomes:

(24)

Exponentiating, we have:

(25)

Through a similar process, we can arrive at

(26)

where

(27)

Exponentiating, we have: exp(ln())exp(ln())

(28)

That leaves us with:

Inserting both of these into equation (20):

(29)

(30)

(31)

Finally, we have:

(32)

(33)

(34)

The two-period rate is a special case of this set of relationships where $A_{32} = 0$. A multi-period rate involving four or more pricing periods can also be derived by analogy, adding appropriate *A* terms.

4.3 MODEL ESTIMATION

The models described in the previous sections can be estimated through regression analysis. Two common regression estimators are ordinary least squares (OLS) and weighted least squares (WLS). The latter estimator allows different observations to have different weights in the regression and can be used to estimate parameters that represent the population as a whole using a stratified sample such as the one we have in the SPP.

Parameters estimated using OLS or WLS are unbiased under fairly general assumptions about the distribution of the error term. However, if the error terms do not conform to the basic assumptions of the classical regression model[61], the usual reported standard errors associated with the parameter estimates may be biased. This can happen, for example, if the error terms are either autocorrelated or heteroscedastic. The error terms are considered to be autocorrelated if the error term in a given time period is correlated with the error term in subsequent time periods. The error terms are considered to be heteroscedastic if they don't display a constant variance across cross-sectional units. [62]

In both cases, the standard error of the parameter estimates would be biased downward which, in turn, would make the t-statistics, which are used to judge the statistical significance of the parameters, biased in an upward direction.[63] Under such circumstances, one could erroneously conclude that time-varying prices are having a statistically significant impact on customer usage when there may be insufficient precision in the estimation to reach a conclusion about statistical significance.

The dataset used for estimating the demand models described in subsequent sections consists of both cross-sectional and time-series observations. Because participants were enrolled in the SPP at different times, the SPP dataset is an unbalanced panel. A balanced panel data set involves repeated observations of the same set of cross-section units, while an unbalanced panel data set involves repeated observations on a varying set of cross-sectional units. The SPP data set for the summer of 2003 is comprised of four months of weekday daily data over the summer for several hundred customers in each cell. Pre-treatment data going back to April also exists for several customers, and data for the month of June exists on almost all customers.

There are several ways in which heteroscedasticity or autocorrelation could arise with panel data. First, heteroscedasticity could arise from different variability across days, households or household-day combinations. Second, there could be serial correlation that arises from un-modeled, but temporally related effects at the household level that decay over time. For example, vacations can cause successive days to exhibit lower than typical usage, but this effect would decay over long time periods. Third, there could be household-specific effects that are not captured by the socio-demographic, economic,

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[61] These assumptions require that the error terms be independently and identically distributed according to the normal distribution with a zero mean and constant variance.

[62] For further discussion of these terms, see any standard textbook on econometrics such as Jack Johnston and John NiNardo, *Econometric Methods*, Fourth Edition, The Mc-Graw Hill Companies, 1997 or William H. Greene, *Econometric Analysis*, Fifth Edition, Prentice Hall, 2003.

[63] The t-statistic is obtained by dividing the mean estimate of a parameter (regression coefficient) by its standard error. A value of 1.96 for this statistic indicates that the parameter estimate is statistically significantly different from zero at a 95% confidence level.

climatic and attitudinal variables, but that persist over the entire analysis period. Such persistent effects would induce autocorrelation at the household level that does not decay over time. Differences in customer lifestyle that are constant over time could create such autocorrelation patterns.

The presence of autocorrelation or heteroscedasticity cannot be easily handled by standard statistical software such as SAS, given the unbalanced panel data set in the SPP. The best way to address these potential problems is to estimate standard errors from more general models that do not make the assumption of homoscedasticity and independence of the error term. If the alternative standard errors are not different from those derived under the basic assumptions of the general linear model, then the problems do not affect the statistical inference about price elasticities of demand, which is the primary focus of the SPP. If they do differ substantially, one or both problems exist and must be accounted for when making statistical inferences.

4.3.1 Diagnostic Analysis

This section summarizes the analysis that was done to diagnose whether autocorrelation and/or heteroscedasticity significantly impact the estimates of standard errors and to correct for these problems if they exist.

Data from the CPP-F treatment and control groups was used to estimate standard errors that are valid in the presence of several types of heteroscedasticity or autocorrelation in the regression model error terms. First, we estimated the standard errors under the assumption of homoscedasticity and temporal independence. Second, we computed standard errors that are valid[64] even if the error term is heteroscedastic. Third, we computed the "Newey-West" standard errors, which are valid if the regression errors exhibit heteroscedasticity and/or autocorrelation that decreases as the time separation between errors increases.[65] Finally, we computed standard errors that are valid if there is autocorrelation that arises from persistent, household-specific components in the regression errors.

The "random effects estimator" was used to implement the final option. This assumes that the error term is comprised of two parts, one that varies by customer but is constant across time while the other part varies with customer and time but is independent and identically distributed. The first part is assumed to be random and not correlated with any of the explanatory variables in the regression equation. In all cases, the standard error estimates were implemented using the matrix programming language GAUSS.

[64] In the following, we refer to standard error estimates as valid if they are asymptotically correct – that is, they correctly estimate standard errors under the proposed model for the regression errors in large samples. Given the large sample sizes, such asymptotic formulas should be very accurate.

[65] The Newey-West standard error formulas have been adjusted to account for the panel structure of the data and to accommodate the use of WLS. For further discussion, consult Whitney K. Newey and Kenneth D. West, 1987, "A Simple, Positive Semi-definite, Heteroskedasticity and autocorrelation Consistent Covariance Matrix," Econometrica Vol. 55 (3) pp. 703-08.

Separate regression models were estimated for peak energy use and off-peak energy use using the double-log model specification. Initially, separate models were estimated for CPP days and non-CPP days using daily data. The regression parameter estimates for peak and off-peak prices (which equal the own and cross-price elasticities, given the logarithmic formulation of the demand equations) and alternative standard error estimates are shown in Tables 4-1 and 4-2.

Table 4-1
WLS Parameter Estimates for Peak-Period Energy Use with Alternative Standard Error Estima
Using Daily Data on CPP Days

Zone	Variable	WLS Parameter Estimate (Daily Data)	H.S. Standard Error *	H.S. Consistent Standard Error	Newey-West Standard Error	Random Effects Standard Error	t Valu Ranc Effe
1	Own-Price	-0.11978	0.04711	0.04342	0.06092	0.08689	-1.
	Cross-Price	-0.38767	0.14684	0.13350	0.18929	0.26715	-1.
2	Own-Price	-0.15806	0.03630	0.03753	0.05322	0.07720	-2.
	Cross-Price	-0.29281	0.10255	0.09287	0.13214	0.19184	-1.
3	Own-Price	-0.37731	0.04316	0.03922	0.05496	0.08117	-4.
	Cross-Price	-0.68517	0.10953	0.09891	0.13491	0.19726	-3.
4	Own-Price	-0.30180	0.04908	0.04267	0.06129	0.09413	-3.
	Cross-Price	-0.49233	0.12154	0.11290	0.16434	0.25311	-1.

Table 4-2
WLS Parameter Estimates for Peak-Period Energy Use with Alternative Standard Error Estima
Using Daily Data on Non-CPP Days

Zone	Variable	WLS Parameter Estimate (Daily Data)	H.S. Standard Error	H.S. Consistent Standard Error	Newey-West Standard Error	Random Effects Standard Error	t Ra Ef
1	Own-Price	-0.11455	0.04199	0.04005	0.06636	0.21759	-
	Cross-Price	-0.27621	0.05026	0.04770	0.07873	0.25348	-
2	Own-Price	-0.11976	0.03168	0.03366	0.05522	0.17204	-
	Cross-Price	-0.09898	0.03295	0.03047	0.04982	0.14571	-
3	Own-Price	-0.64590	0.03854	0.03443	0.05613	0.16777	-
	Cross-Price	-0.52312	0.03398	0.03042	0.04952	0.14539	-
4	Own-Price	-0.36166	0.04051	0.03655	0.06074	0.19410	-
	Cross-Price	-0.14072	0.03687	0.03899	0.06632	0.21391	-

* H.S.-Heteroscedastic

Table 4-1 corresponds to peak-period energy use on CPP days and Table 4-2 to peak-period energy use on non-CPP days. Similar models were estimated for off-peak energy use and yielded generally similar findings with regard to the impact on the estimated standard errors. In Table 4-1, the peak price is the critical peak price and in Table 4-2, it is the (standard) peak price.

In all cases shown in Tables 4-1 and 4-2, there is no substantial difference in the estimated standard errors between the first two columns, suggesting that heteroscedasticity of the error term does not, by itself, lead to biased standard error estimates in the SPP dataset. This is not surprising, since the experimental prices were assigned randomly to customers and so, should not be correlated with any plausible pattern of heteroscedasticity in the error term.

The Newey-West standard errors are about 25-30 percent higher than the original “homoscedastic” standard errors for CPP days and about 40-60 percent higher for non-CPP days. The impact of the Newey-West adjustment is larger for the non-CPP days because there are many more non-CPP days than CPP days in the sample (74 days versus 12 days). However, further analysis of the residuals from the regressions indicated that these Newey-West standard errors were still under-estimating the true standard errors. In the SPP data set, most of the unexplained variance is cross-sectional rather than temporal, which leads to a persistent pattern for the autocorrelations in the error terms over time. The “Random Effects” estimator adjusts for such a pattern of autocorrelation in the errors.

Application of the random effects model yields standard errors that are roughly 80-90 percent higher than the original WLS standard errors for CPP days and 300-400 percent higher for non-CPP days. Random effects standard errors that are substantially larger than those computed using the WLS formulas usually indicate that additional precision can be achieved by using a generalized least squares (GLS) estimator. However, in our case we cannot implement random effects GLS estimation for a specification that includes variables representing customer characteristics because all of the explanatory variables except for weather are constant over time. Since almost all of the variation in the dataset is cross-sectional in nature, it is technically infeasible to estimate the parameters associated with a GLS model that embodies the random effects model and includes all the survey data, given that we are working with an unbalanced panel.

An alternative approach that allows for inclusion of customer-specific effects involves averaging energy use across days rather than using daily data. Tables 4-3 and 4-4 contain results for the day-type models using average daily energy use across the entire summer for each day type. The first column in each table reproduces the WLS estimates from Tables 4-1 and 4-2, which are based on daily data.[66] The second column shows the same parameter estimates but reports standard errors that are derived from the Random Effects model described above. The third column shows the results from applying the WLS estimator to average daily data.

[66] These are taken from Tables 5-2 and 5-3 in the March 9 report.

Table 4-3 Price Elasticities of Demand for Peak-Period Energy Use CPP-F Rate on CPP Days, Treatment Period			
Climate Zone	Peak Period Own-Price Elasticities		
	WLS Daily Data	WLS with Random Effects Standard Errors	Daily Average Model
Zone 1	**-0.12** ***(-2.83)***	-0.12 *(-1.38)*	-0.16 *(-1.54)*
Zone 2	**-0.16** ***(-5.10)***	**-0.16** ***(-2.05)***	**-0.15** ***(-1.97)***
Zone 3	**-0.38** ***(-10.34)***	**-0.38** ***(-4.65)***	**-0.37** ***(-4.27)***
Zone 4	**-0.30** ***(-6.88)***	**-0.30** ***(-3.21)***	**-0.30** ***(-2.81)***

Table 4-4 Price Elasticities of Demand for Peak-Period Energy Use CPP-F Rate on Non-CPP Days, Treatment Period			
Climate Zone	Peak Period Own-Price Elasticities		
	WLS Daily Data	WLS with Random Effects Standard Errors	Daily Average Model
Zone 1	-0.11 *(-3.03)*	-0.11 *(-0.53)*	-0.20 *(-0.86)*
Zone 2	-0.12 *(-4.42)*	-0.12 *(-0.70)*	-0.03 *(-0.22)*
Zone 3	-0.65 *(-19.85)*	-0.65 *(-3.85)*	-0.62 *(-3.33)*
Zone 4	-0.36 *(-9.98)*	-0.36 *(-1.86)*	-0.39 *(-1.84)*

As seen in Table 4-3, on CPP days there is very little difference between the parameter estimates using the WLS model and daily data and the WLS model with average data. The largest percent difference in the own-price elasticity is in zone 1, where the estimates are –0.12 using daily data and –0.16 when the estimate is based on average daily data. This demonstrates clearly that the daily variation in energy use does not significantly influence the estimation of the price elasticity. There is, of course, considerable variation in the t-statistics in column 1 versus those in columns 2 and 3. The t-statistics in columns 2 and 3 are about half the size of those in column 1. Importantly, the own-price elasticities are still significant in Zones 2, 3 and 4. Also important is the comparison of the standard errors in the last two columns, which are generally comparable, indicating that this relatively simple, averaging approach produces unbiased estimates comparable to those of the more complex random effects model.

Correcting the estimated standard errors for autocorrelation has a much larger impact on the non-CPP day models shown in Table 4-4 than it does on the CPP-day models (for the reasons explained previously). The t-statistics in Table 4-4 drop approximately by a factor of five in columns 2 and 3 compared to column 1. Parameter estimates don't vary much across the three columns in Table 4-4, except in Zone 2, where the last column differs considerably from the other two columns. However, since the t-statistics have dropped appreciably, the only statistically significant price elasticity is in Zone 3.
One possible explanation for the insignificant price elasticities on non-CPP days is that the impact on energy use of these relatively small price ratios on non-CPP days (compared with the ratios on CPP days) is swamped by the unexplained variation in energy use across households. If so, it might be possible to obtain statistically significant estimates for the price elasticity by introducing more price variation into the estimating sample and, in particular, more longitudinal variation in price, since the longitudinal variation in price would not be swamped by the cross-sectional variation in energy use. Given the current experimental design and data, there are several ways to introduce more price variation into the estimating sample. One is to combine the CPP and non-CPP day types; another is to combine pre-treatment data with treatment data; a third is to pool across both day types and treatment periods; and a fourth is to pool across climate zones. Below, we examine the first three.[67]

The last column in Table 4-5 contains the estimated parameters and standard errors for the own-price elasticity based on the WLS model pooling across day-types. The first two columns in Table 4-5 repeat the day-type estimates presented previously. As seen, the elasticity values are generally smaller than the day-type estimates, but they are statistically significant in three of the four zones, whereas the non-CPP day estimates were only statistically significant in Zone 3. However, these results are now subject to the problem of autocorrelation across the two day- types (although the impact should be small since there are only two observations for each customer rather than the 80 or so observations for each customer before averaging was introduced). In order to eliminate this problem, we re-estimated the parameters using the random effects model. At this stage of the analysis, we also introduced pre-treatment data into the estimation sample

[67] As seen in Section 5, we ultimately pooled data across climate zones as well. However, this had more to do with examining differences across zones due to variation in air conditioning saturation and weather rather than the small differences in average price across zones.

in order to allow us to test whether or not the data could indeed be pooled by day type and to give us another source of price variation.[68, 69]

Table 4-5 WLS Price Elasticities of Demand for Peak-Period Energy Use CPP-F Rate with Average Data, Treatment Period			
	Peak Period Own-Price Elasticities		
Climate Zone	CPP Days	Non-CPP Days	All Weekdays
Zone 1	**-0.16** ***(-1.54)***	-0.20 *(-0.86)*	-0.09 *(-1.40)*
Zone 2	**-0.15** ***(-1.97)***	-0.03 *(-0.22)*	**-0.10** ***(-2.08)***
Zone 3	**-0.37** ***(-4.27)***	**-0.62** ***(-3.33)***	**-0.26** ***(-4.46)***
Zone 4	**-0.30** ***(-2.81)***	-0.39 *(-1.84)*	**-0.21** ***(-3.01)***

The analysis was carried out with the SAS software package, using the TSCS regression procedure. Three day types were included in the analysis, the average of all pre-treatment days, the average of CPP days and the average of non-CPP days. We tested whether or not the data could be pooled by including a binary variable representing CPP day interacted with price. In all cases, the interaction term was statistically insignificant, indicating that day types could indeed be pooled. The pooled results are shown in Table 4-6, which contains both the own-price elasticity and the cross-price elasticity for peak usage. Three sets of results are reported, corresponding to weighted least squares, the random effects model and the fixed effects model. The WLS results are subject to the problem of autocorrelation while the other two are not. Survey data on individual customers is included in the WLS and random effect models while the fixed effects model includes a dummy variable that is specific to each customer. All the models have been estimated with average data by day type.

Table 4-6
Price Elasticities of Demand for Peak-Period Energy Use
CPP-F Rate on All Weekdays with all Pretreatment Data

[68] Table 4-6 computes average daily usage for the pretreatment period based on data only from the month of June, whereas Table 4-7 includes all the pre-treatment data in the daily average computation. There is much more consistency across consumers in the number of days underlying the average value when only the June data are used than when all pretreatment data are used, because most customers have June data whereas many do not have May or April data. As seen in Table 4-6, there is not much difference in the results between the two approaches. Hereafter we rely on the June average data since this results in a more homogeneous sample across customers that is not subject to measurement error.

[69] Without the pre-treatment data in the sample, it is difficult to test for any difference in response between the CPP and non-CPP days, since the off-peak price does not vary much between those two days.

	WLS Model		Random Effects Model		Fixed Effects Model	
	Own-Price Elasticity	Cross-Price Elasticity	Own-Price Elasticity	Cross-Price Elasticity	Own-Price Elasticity	Cross-Price Elasticity
Zone 1	-0.08 *(-1.24)*	-0.34 *(-1.91)*	-0.007 *(-0.25)*	-0.09 *(-0.95)*	-0.03 *(-1.10)*	-0.18 *(-1.70)*
Zone 2	**-0.08** ***(-1.75)***	-0.09 *(-0.79)*	**-0.11** ***(-4.94)***	**-0.21** ***(-3.21)***	**-0.09** ***(-4.30)***	**-0.18** ***(-2.94)***
Zone 3	**-0.25** ***(-4.90)***	**-0.43** ***(-3.41)***	**-0.15** ***(-5.59)***	**-0.27** ***(-3.64)***	**-0.17** ***(-6.22)***	-0.09 *(-1.29)*
Zone 4	**-0.14** ***(-2.30)***	-0.19 *(-1.30)*	**-0.18** ***(-4.95)***	**-0.19** ***(-2.21)***	**-0.24** ***(-6.99)***	**-0.20** ***(-2.47)***

Table 4-7
Price Elasticities of Demand for Peak and Off-Peak Energy Use
CPP-F Rate on All Weekdays with all Pretreatment Data
Fixed Effects with Average Data

Climate Zone	Peak Period		Off Peak Period	
	Own-Price Elasticity	Cross-Price Elasticity	Own-Price Elasticity	Cross-Price Elasticity
Zone 1	-0.04 *(-1.43)*	-0.18 *(-1.81)*	**-0.19** ***(-2.55)***	+0.02 *(+0.93)*
Zone 2	**-0.09** ***(-4.23)***	**-0.17** ***(-2.83)***	**-0.09** ***(-2.02)***	-0.001 *(-0.07)*
Zone 3	**-0.18** ***(-6.45)***	-0.12 *(-1.66)*	-0.07 *(-1.35)*	-0.01 *(-0.44)*
Zone 4	**-0.24** ***(-7.15)***	**-0.19** ***(-2.34)***	**-0.19** ***(-3.67)***	-0.03 *(-1.31)*

Based on the analysis summarized above, a decision was made to use the fixed effects model. The fixed effects model is one of the most widely used specifications in the analysis of panel data. It corrects for the majority of autocorrelation and heteroscedasticity present in this situation by accounting for both the observed and unobserved differences across customers. Furthermore, the specification allows for the inclusion of interaction terms that would allow the price elasticities of demand to vary with factors such as the ownership of central air conditioners.

A decision was also made to use average daily data by rate period rather than the daily data. Because there is no variation in prices across days, except the variation across day-types (e.g., CPP and non-CPP days for the CPP rate) and across pretreatment and treatment periods, there is no loss of explanatory power when the data is pooled across days of the same type. The parameter estimates are very similar based on daily data and average daily data but the estimated standard errors using average data are not biased due to autocorrelation or heteroscedasticity.

Finally, in order to increase the amount of price variation that underlies the price elasticity estimates, we tested whether data could be pooled across day types whenever prices vary (e.g., for the CPP rates). We found that the elasticities were not significantly different across day types so that the data could be pooled. Pooling across both the treatment and pretreatment period adds additional price variation and improves the estimates and, thus, is also recommended.

Although the approach summarized above solved most of the problems that existed with the estimated presented in previous version of this report, there may still be some residual correlation in the error terms that would lead to slightly biased estimates of the standard errors. To investigate this possibility, we performed some additional diagnostic testing with the residuals from the CES demand model for the CPP-F rate. The model specification consists of a price ratio term, a linear weather term, an interaction term between price and CAC saturation, an interaction term between price and weather and fixed effect terms for each customer. The specification was reported earlier in this section as equation (3). The 15-observation database described in Section 5 was used for this analysis.

Appendix 10 contains a 15x15 correlation matrix of residuals. The correlations of interest are displayed in the off-diagonal elements of the matrix. In absolute terms, 80% of the correlations in this matrix are under 0.3 and 95 percent under 0.4. It's our opinion that there is some residual serial correlation in the data. However, the pattern of serial correlation is complex and cannot be easily remedied with estimation procedures in SAS. Based on a rough "back of the envelop" calculation, the standard errors may have a downward bias of about 30 percent.

Appendix 10 also has a second table containing a covariance matrix of residuals. Examination of this matrix suggests that there is a small amount of heteroscedasticity in the residuals. The variance on non-CPP days has a value that is about a third to a half of the size of the variance on CPP days. The variance on pre-treatment days is about the same as the variance on CPP days. Weighting the data by taking the square root of the number of days won't solve the problem since there is evidence of serial correlation in the data, which tends to over-state the influence of the number of days. This remaining heteroscedasticity may lead to an under-estimate of the standard errors of about 20 percent.

Combining the impact of the two factors, the standard errors in the demand model may be biased downward by about 50 percent. This suggests that the t-statistics are possibly biased upward by 33%. This fact should be kept in mind when interpreting the empirical results reported in subsequent sections of this report. We hope to study this issue further in the Summer 2004 analysis.

4.3.2 SELF-SELECTION BIAS IN THE SAMPLE

A key issue in analyzing the impact of time-differentiated rates in the SPP is whether or not the results can be generalized to the target population. For CPP-F and TOU customers in Track A, the target population consists of the entire population in each climate zone and, ultimately, throughout the state. If the enrolled sample is not representative of the target population, it is important to correct for any differences in energy use between the treatment and control customers that existed prior to the treatment going into effect. Such preexisting differences may result from self-selection (e.g., consumers who use less energy during the peak period might enroll at a higher rate), differences in sample selection, outliers, differences in the enrollment process, or any of a host of reasons.

When testing and adjusting for selection bias, it is very important to distinguish between two types, one due to observable variables and the other due to unobservable variables. For example, assume that households that enroll in the experiment have higher energy use than those that do not enroll, but this difference is due entirely to the fact that enrolled households have higher levels of air conditioner use. Assume also that, after accounting for these differences in air conditioner saturation rates, the demand for electricity is the same between enrolled and non-enrolled households. Under these assumptions, if the saturations for each group are known, then adjustments can be made for the selection bias by controlling for differences in air conditioner saturation when estimating treatment impacts or demand models.

On the other hand, if the preexisting difference between enrolled and non-enrolled customers is due to factors that cannot be observed, adjustments must be made in the impact estimates or demand models. Intuitively, the reason is that the observed, treatment-period estimates and estimated price elasticities will reflect not only the true responsiveness of an individual household's demand to changes in price, but also the impact that the price treatment had on enrollment.

The issue of selection bias is addressed in the analysis presented in the following sections in two ways. First, we have included data from the pre-treatment period in the regression model. Thus, the regression parameters net out any unobservable, pre-existing differences between treatment and control customers. Second, we have used the fixed effects estimation procedure. The fixed effect variable also controls for unobservable differences across customers. Given these two factors, we are confident that the elasticities reported here are not biased by any self-selection bias that might exist in the estimation sample. We are also encouraged by the fact that a comparison of energy use among treatment and control customers does not indicate any significant bias in the sample. We combined data on average daily usage (ADU) for the summer of 2002 (e.g., prior to the SPP going into effect) from the three investor-owned utilities to calculate the mean and standard deviation for the SPP samples by cell. We then compared the sample values with the corresponding population values by climate zone, dwelling type, and usage level.

A key issue is whether or not the sample mean value for ADU in each climate zone, dwelling type, usage level and cell is significantly different from the population mean. Since the population variance is known, we can use the Z-test, instead of the t-test, to investigate this issue. The Z-test depends on the sample size, the difference between the sample mean and the population mean, and the population standard deviation.

Table 4-8 shows the values for the Z-test and its p-value along with the mean and standard deviation for the sample and the population by climate zone, dwelling type, usage level, and cell. The p-value represents the smallest level of significance that would lead to the rejection of the following null hypothesis, "There is no difference between the population mean and the sample mean".

The Z-test is significant at .05 if p-value < .05. All the p-values in Table 1 are greater than .05. Thus one can conclude that there is insufficient evidence to reject the null hypothesis. In other words, the sample and population means are not statistically different from each other based on average daily electricity use.

Table 4-8
Comparison of ADU for the Population and the Sample

			Population			Sample						
Climate Zone	Dwelling	Usage	Count	Mean	Standard Deviation	Cell	Rate Level	Size	Mean	Standard Deviation	Z-Test	P-value
1	SF	Low	432,337	9.350	3.888	A01	All	17	9.634	3.224	0.301	0.7638
						A05	High	7	9.348	2.298	0.001	0.9988
						A05	Low	9	11.441	4.909	1.613	0.1067
						A13	High	8	9.956	4.799	0.441	0.6592
						A13	Low	6	9.137	2.045	0.134	0.8931
		High	199,754	24.166	13.843	A01	All	20	22.067	6.092	0.678	0.4977
						A05	High	11	19.021	6.588	1.233	0.2177
						A05	Low	10	22.838	7.892	0.304	0.7615
						A13	High	8	24.070	7.723	0.020	0.9843
						A13	Low	12	21.372	6.122	0.699	0.4844
	MF	All	420,389	8.108	6.263	A01	All	24	7.618	4.634	0.384	0.7012
						A05	High	11	9.145	5.927	0.549	0.5829
						A05	Low	11	9.896	7.266	0.946	0.3440
						A13	High	13	6.895	3.999	0.699	0.4848
						A13	Low	9	8.719	3.502	0.293	0.7698
2	SF	Low	1,705,337	11.317	4.439	A02	All	25	12.169	4.430	0.959	0.3378
						A06	High	28	11.921	4.547	0.720	0.4717
						A06	Low	27	11.709	4.087	0.458	0.6467

Table 4-8
Comparison of ADU for the Population and the Sample

			Population			Sample						
Climate Zone	Dwelling	Usage	Count	Mean	Standard Deviation	Cell	Rate Level	Size	Mean	Standard Deviation	Z-Test	P-value
						A11	All	16	13.007	5.122	1.522	0.1280
						A14	High	4	7.301	3.382	1.810	0.0703
						A14	Low	8	11.023	4.564	0.188	0.8510
						A02	All	42	30.922	11.421	0.136	0.8916
						A06	High	47	29.622	13.995	0.369	0.7120
		High	932,653	30.557	17.362	A06	Low	41	28.802	9.205	0.647	0.5176
						A11	All	33	28.716	7.849	0.609	0.5426
						A14	High	13	28.633	8.967	0.399	0.6896
						A14	Low	9	31.777	8.831	0.211	0.8330
						A02	All	25	11.156	5.338	0.716	0.4738
						A06	High	21	11.013	4.634	0.562	0.5738
	MF	All	1,312,896	10.153	7.003	A06	Low	32	9.941	6.057	0.171	0.8643
						A11	All	17	8.824	4.433	0.783	0.4339
						A14	High	8	11.445	4.684	0.522	0.6017
						A14	Low	11	9.289	3.453	0.409	0.6825
						A03	All	27	15.417	7.463	0.863	0.3880
						A07	High	33	15.901	4.655	1.446	0.1482
3	SF	Low	1,241,899	14.476	5.664	A07	Low	38	15.465	6.100	1.077	0.2816
						A12	All	20	16.763	5.872	1.806	0.0709
						A15	High	8	15.382	3.300	0.453	0.6509
						A15	Low	8	14.313	5.090	0.081	0.9353
						A03	All	49	38.680	10.685	0.672	0.5015
						A07	High	47	36.763	15.802	0.171	0.8642
		High	930,519	37.158	15.852	A07	Low	46	37.719	10.729	0.240	0.8104
						A12	All	35	36.711	11.104	0.167	0.8673
						A15	High	16	36.976	11.682	0.046	0.9634
						A15	Low	12	39.531	11.538	0.518	0.6042
						A03	All	22	13.060	6.740	0.522	0.6018
	MF	All	649,469	14.131	9.625	A07	High	23	15.392	8.500	0.628	0.5299
						A07	Low	20	13.628	9.929	0.234	0.8153

Table 4-8 Comparison of ADU for the Population and the Sample												
			Population			Sample						
Climate Zone	Dwelling	Usage	Count	Mean	Standard Deviation	Cell	Rate Level	Size	Mean	Standard Deviation	Z-Test	P-value
						A12	All	13	16.090	10.587	0.734	0.4631
						A15	High	6	13.954	6.179	0.045	0.9640
						A15	Low	4	21.776	16.620	1.589	0.1122
4	SF	Low	408,266	16.575	7.143	A04	All	26	17.955	7.757	0.986	0.3243
						A08	High	16	16.625	7.566	0.028	0.9777
						A08	Low	22	17.023	6.267	0.294	0.7685
						A16	High	7	18.515	5.749	0.719	0.4723
						A16	Low	7	17.374	7.226	0.296	0.7672
		High	319,255	44.448	19.585	A04	All	53	45.259	18.465	0.302	0.7629
						A08	High	31	43.969	17.441	0.136	0.8918
						A08	Low	28	44.573	14.062	0.034	0.9729
						A16	High	15	49.949	27.853	1.088	0.2766
						A16	Low	11	43.070	13.080	0.233	0.8155
	MF	All	190,914	20.362	12.706	A04	All	20	22.432	12.478	0.729	0.4662
						A08	High	14	19.911	9.975	0.133	0.8945
						A08	Low	12	21.664	13.609	0.355	0.7226
						A16	High	5	26.014	12.184	0.995	0.3198
						A16	Low	7	21.490	8.974	0.235	0.8143

5. Residential Demand Models And Impact Estimates

This section summarizes the empirical analysis that has been completed for the Track A, CPP-F and TOU rate treatments and the Track C CPP-V rate treatment. The empirical results for the Track B CPP-F and informational treatments will be summarized in a separate report to be written prior to the end of 2004. As discussed in section 2, recruitment into the Track A CPP-V residential rate treatment was aborted in June 2003. Recruitment was started again in spring 2004 and results for this treatment will be presented in the final SPP report, which will cover results for both summer 2003 and 2004 and for the winter 2003/2004 time period. Analysis of the information-only treatment will also be summarized in the final report. Section 5.1 presents results for the CPP-F tariff, section 5.2 discusses the TOU tariff and section 5.3 summarizes the analysis for the CPP-V tariff.

5.1 CPP-F RATE ANALYSIS

This section summarizes the analysis based on the CPP-F treatment group. Section 5.1.1 discusses the demand models, price elasticities and impact estimates for weekday peak and off-peak energy demand. Section 5.1.2 continues this analysis by assessing how price responsiveness varies with weather and section 5.1.3 discusses how price responsiveness varies with customer characteristics. Section 5.1.4 shows how energy use varies with price with graphical demand curves and section 5.1.5 examines energy use and demand response on weekends and holidays.

5.1.1 WEEKDAY ANALYSIS

The final results summarized in this section reflect an evolution of analysis. Demand models were initially estimated separately for each climate zone for the CPP-F rate treatment. In the majority of regressions, price was statistically significant and price elasticities and elasticities of substitution were found to be comparable to those in the literature. Demand responsiveness was found to be greater in hotter climate zones (zones 3 and 4) than in cooler zones (zones 1 and 2).

Ultimately, the data was pooled across climate zones and the model specification was modified to include interaction terms between weather and price and a variable representing central air conditioning (CAC) ownership and price. These interaction terms allow price responsiveness to vary with weather and air conditioning ownership. Once these two factors are accounted for, no statistically significant differences were found across climate zones. That is, price responsiveness varies across climate zones because of differences in weather and air conditioning ownership. The zonal differences in price elasticities and impacts reported below are based on the pooled database with weather/price and air conditioning/price interaction terms included in the specification.

5. Residential Demand Models and Impact Estimates

The results presented here are based on a 15-observation database. This database consists of observations pooled across CPP and non-CPP days during the treatment period and all June pretreatment days. An interaction term between the price variable and a binary variable representing CPP days was initially included in the demand models to test whether response differed on CPP and non-CPP days. When both weather and CAC saturations were included in the model specification, there was no statistically significant difference between responsiveness on CPP and non-CPP days. Stated another way, while there are small differences in responsiveness on CPP and non-CPP days, these are due solely to the influence of weather on price response (which is discussed further in section 5.1.2). Once the difference in weather on CPP and non-CPP days is accounted for, there is no additional difference in price responsiveness on the two day types.[70]

Table 5-1 presents the summary measures of price response from the CES model specification based on analysis of the CPP-F treatment. Table 4-2 summarizes the average air conditioning saturations and weather variable values underlying the estimates in Table 5-1. Recall from section 4.2.1 that the weather term in the elasticity of substitution equation equals the difference in cooling degree hours per hour in the peak period and off-peak periods and the weather term in the daily energy equation is daily cooling degree hours per hour.

As seen in Table 5-1, the average elasticity of substitution across all climate zones equals -0.069 and the average price elasticity of daily energy use on weekdays is –0.023. The elasticity of substitution increases significantly across climate zones, from a low of -0.032 in zone 1 to a high of -0.111 in zone 4. The weekday, daily price elasticity is much more constant across climate zones. The differences in price responsiveness are small between CPP and non-CPP days. Overall, there is about a 15 percent difference in the value of the elasticity of substitution on CPP days relative to non-CPP days.

[70] It should be kept in mind, of course, that the same degree of responsiveness does not mean that impacts are the same on each day type, as both prices and average energy use for control customers vary across day types so the absolute impact on CPP days will be significantly larger than on non-CPP days.

Table 5-1 Summary Measures For Price Responsiveness CES Model Specification[71]						
Climate Zone	Elasticity of Substitution (Weekday Peak to Off-Peak Electricity Use)			Price Elasticity for Daily Weekday Electricity Use		
	CPP Days	Non-CPP Days	All Week-days	CPP Days	Non-CPP Days	All Week-days
1	-.045	-.030	-.032	-.041	-.037	-.037
2	-.061	-.053	-.054	-.029	-.026	-.027
3	-.099	-.091	-.092	-.014	-.010	-.011
4	-.121	-.109	-.111	-.032	-.024	-.025
All	-.077	-.067	-.069	-.026	-.023	-.023

Table 5-2 Air Conditioning and Weather Data Underlying Elasticity of Substitution And Daily Price Elasticities							
Climate Zone	CAC Saturation	Peak CDH/hr – Off-Peak CDH/hr			Daily CDH/hr		
		CPP Days	Non-CPP Days	All Week-days	CPP Days	Non-CPP Days	All Week-days
1	0.064	4.134	1.409	1.759	1.639	.436	0.590
2	0.292	5.742	4.347	4.542	2.390	1.665	1.766
3	0.673	10.640	9.058	9.279	5.514	4.345	4.509
4	0.724	14.365	12.166	12.474	12.582	10.027	10.385
All	0.422	7.899	6.120	6.433	4.291	3.183	3.336

Table 5 contains estimates of the own-and cross-price elasticities of energy use by rate period based on the double-log (DL) model specification using average weather for all weekdays.[72] As seen in the table, the own-price elasticity of demand for peak-period energy use also varies across climate zones, from a low of –0.055 in climate zone 1 to a high of –0.139 in climate zone 4. The average, statewide value is –0.094. The average cross-price elasticity of demand for peak-period energy use, given a change in off-peak

[71] Determining the statistical significance of these summary variables is complex because they are comprised of three terms in the regression model (e.g., the price term by itself as well as the two interaction terms described in the text). Each of these terms by itself is statistically significant at the 95 percent confidence level.

[72] The differences on CPP and non-CPP days are similar to those for the CES model. Since the differences across day types are so small, they are not included in the table.

price, equals –0.140, indicating that peak-period energy use will fall given an increase in off-peak prices and vice versa.

Table 5-3 Summary Measures of Price Responsiveness Double-Log Model Specification[73]			
Climate Zone	Rate Period	Price	
		Peak	Off-Peak
Zone 1	Peak	-.055	-.077
	Off-Peak	-.001	-.127
Zone 2	Peak	-.077	-.116
	Off-Peak	+.006	-.146
Zone 3	Peak	-.116	-.183
	Off-Peak	+.016	-.172
Zone 4	Peak	-.159	-.206
	Off-Peak	+.014	-.139
All	Peak	-.094	-.140
	Off-Peak	+.009	-.151

The average own-price elasticity of demand for off-peak energy use is -.151. The zone-specific values range from a low of -.127 in zone 1 to a high of -.172 in zone 3. The cross-price elasticity of demand for off-peak energy use as a function of peak period price is quite small, with the statewide average only equal to approximately +.01.

Table 5-4 summarizes the impact of the average SPP CPP-F rate on energy use in each rate period on CPP and non-CPP weekdays. The vast majority of the difference in impacts on CPP and non-CPP days is due to differences in prices on those days. As previously discussed, a much smaller influence is the difference in elasticities resulting from differences in weather across day types.

As seen in Table 5-4, the reduction in peak-period energy use resulting from the SPP tariffs ranges from a low of –8.35 percent in climate zone 1 to a high of –17.13 percent in zone 4. The statewide average equals –12.50 percent. Off-peak, CPP-day energy use increases slightly in three out of four zones, with the statewide increase equaling +3.04 percent. The change in daily energy use on CPP days is small but negative.

The change in peak-period energy use on non-CPP days is roughly 60 percent less than the change on CPP days, with a statewide average reduction of –4.80 percent. The difference in percent impacts between CPP and non-CPP days varies across climate zones. For example, in zone 1, the non-CPP day reduction is about 80 percent less than the CPP day reduction while in zone 4, the difference is only about 40 percent. The increase in off-peak energy use on non-CPP days is comparable to what it is on CPP

[73] See footnotes 7 and 8.

days, with a statewide average increase equal to 1.94 percent. Overall, there is a very slight increase in energy use on non-CPP days.

Table 5-4
Impact Estimates For Average CPP-F SPP Tariff
CES Model Specification

Climate Zone	Impact Measure	CPP Day			Non-CPP Day		
		Peak	Off-Peak	Daily	Peak	Off-Peak	Daily
Zone 1	Base Use (kWh/hr)	0.49	0.46	0.47	0.48	0.46	0.46
	Change (kWh/hr)	-0.04	+0.00	-0.01	-0.01	+0.00	+0.00
	% Change	-8.35	-0.12	-1.94	-1.91	+0.82	+0.23
Zone 2	Base Use (kWh/hr)	0.84	0.63	0.68	0.78	0.61	0.65
	Change (kWh/hr)	-0.08	+0.01	-0.01	-0.03	+0.01	+0.00
	% Change	-9.61	+1.30	-1.53	-3.32	+1.29	+0.12
Zone 3	Base Use (kWh/hr)	1.65	0.95	1.10	1.45	0.88	0.99
	Change (kWh/hr)	-0.22	+0.05	-0.01	-0.08	+0.02	+0.00
	% Change	-13.37	+4.80	-0.90	-5.59	+2.44	+0.01
Zone 4	Base Use (kWh/hr)	2.02	1.15	1.33	1.79	1.06	1.21
	Change (kWh/hr)	-0.35	+0.05	-0.03	-0.12	+0.07	+0.00
	% Change	-17.13	+4.77	-2.14	-6.83	+3.07	+0.02
All Zones	Base Use (kWh/hr)	1.16	.76	.84	1.05	0.72	0.79
	Change (kWh/hr)	-0.15	+0.02	-0.02	-0.05	+0.01	+0.00
	% Change	-12.50	+3.04	-1.42	-4.80	+1.95	+0.07

5.1.2 Impact of Weather on Price Response

An important policy question concerns whether demand response increases or decreases on hot days when the supply system is stressed, or is more or less constant across all summer weather conditions. Determining whether price responsiveness is higher or lower on high-system load days compared with average or cool days is important since the benefits from price response during peak periods are greater on hotter days when load conditions are high than on other days. If price responsiveness degrades on these days, the magnitude of benefits will be less than if responsiveness increases or stays the same as on typical days.

In order to investigate how price response varies with weather, the pretreatment and treatment data were averaged across days (by day type in the treatment period) that were sorted based on system load. For example, the top 20 percent of CPP days (e.g., the top quintile) and the top 20 percent of non-CPP days based on statewide system load were identified and then energy use for each customer was averaged across each of these day types to form two quintiles, one each for CPP and non-CPP days. Averages were computed for each load quintile by day type, forming 15 time-series averages for each customer (e.g., 5 pretreatment average days, 5 average CPP days and 5 average non-CPP days). Next, values for relevant weather variables were computed for each set of averages and these were used in the regressions. In most instances, within each climate zone, the top quintiles and bottom quintiles based on system load corresponded to the hottest and coolest days, respectively. However, in some instances, some other quintile was actually the hottest period. For example, in climate zone 1, which is subject to fog in the summer time when inland climates are quite warm, the fourth quintile based on statewide system load was actually the hottest quintile. Throughout the rest of this section, whenever we refer to the hottest or coolest quintile, this designation is based on the weather in each specific climate zone, not on statewide system load. Thus, the impacts cannot be added across climate zones to get the statewide average impact in all instances, because the top and bottom quintiles actually represent different days.

Table 5-5 summarizes the cooling degree hours associated with CPP and non-CPP days on average days and on the hottest and coolest quintile days. These values and associated other weather variables underlie the impact estimates contained in Tables 5-6 and 5-7. The values in the table highlight the extensive diversity of the state's climate and the differences in weather across the hottest and coolest days during the summer period.

Table 5-5
Average Cooling Degree Hours per Hour

Climate Zone	CPP Days			Non-CPP Days		
	Average Weather	Hottest Quintile	Coolest Quintile	Average Weather	Hottest Quintile	Coolest Quintile
1	1.64	4.86	0.07	1.42	0.61	0.24
2	2.39	3.48	1.50	1.66	2.84	0.44
3	5.51	7.19	3.27	4.35	5.60	1.40
4	12.58	17.57	5.21	10.03	13.84	3.96
All	4.26	6.17	2.23	3.28	4.50	1.06

Tables 5-6 and 5-7 show the relationship between weather and price responsiveness for peak and off-peak load periods, respectively. As seen in Table 5-6, the percent impact is greater on the hottest days than it is on the coolest days. Statewide, the percent reduction in peak period energy use on CPP days is 32 percent greater on the hottest two CPP days than on the coolest two days. The difference is more than two-fold in climate zone 1 and is roughly equal to 27 percent in zones 2 and 4. These estimates should alleviate the concern that customers do not respond to prices on the hottest days—not only do they respond, but the response is even greater on these days than on cooler days. This pattern of response is true on both CPP and non-CPP days, although the differential is smaller on non-CPP days, when the price incentive is significantly smaller, than on CPP days.

Table 5-6
Variation in Peak-Period Energy Impacts Based on Differences in Weather

Climate Zone	Percent Change in Peak-Period Energy Use on CPP Days			Percent Change in Peak-Period Energy Use on Non- CPP Days		
	Average Weather	Hottest Quintile	Coolest Quintile	Average Weather	Hottest Quintile	Coolest Quintile
1	-8.35	-13.75	-5.21	-1.91	-2.05	-1.70
2	-9.61	-10.90	-8.57	-3.32	-4.07	-2.38
3	-13.37	-14.52	-11.15	-5.59	-6.66	-3.99
4	-17.13	-18.67	-14.67	-6.83	-7.34	-5.66
All	-12.50	-13.99	-10.59	-4.80	-5.60	-3.59

Table 5-7
Variation in Off-Peak Energy Impacts Based on Differences in Weather

Climate Zone	Percent Change in Off-Peak Energy Use on CPP Days			Percent Change in Off-Peak- Energy Use on Non- CPP Days		
	Average Weather	Hottest Quintile	Coolest Quintile	Average Weather	Hottest Quintile	Coolest Quintile
1	-0.12	0.81	-0.72	0.82	0.86	0.76
2	1.30	1.51	1.13	1.29	1.56	0.94
3	4.80	4.84	4.44	2.44	2.92	1.73
4	4.77	4.02	5.82	3.07	3.32	2.53
All	3.04	3.09	2.97	1.95	2.27	1.46

5.1.3 Impact of Customer Characteristics on Price Response

Understanding how price responsiveness varies with differences in selected customer characteristics can be useful from both a policy and marketing perspective. For example, if high users are more responsive than low users, different tariffs might be targeted at each customer segment in order to maximize demand response and/or minimize implementation costs. If swimming pool owners are more responsive than households that do not have swimming pools, it may be possible to improve overall demand response from a voluntary program by targeting pool owners.

5. Residential Demand Models and Impact Estimates

The impact on price responsiveness of the following variables was examined using the CES model specification and interaction terms between the price variable and a variable representing each characteristic:

- Average daily energy use in Summer 2002
- A high user binary variable where the threshold for high use varies across climate zones[74]
- Central air conditioning ownership
- Housing type (single family versus other)
- Number of bedrooms in the house
- Annual income
- Swimming pool ownership
- Spa ownership
- Electric cooking ownership
- Whether or not the head of household is a college graduate
- Persons per household.

A statistically significant coefficient on the interaction term for each variable indicates that price response varies between customers who either own or don't own a particular end use represented by the variable or between customers that have different values for a particular continuous variable (e.g., households with two or four bedrooms or high income and low income households). On the other hand, and importantly, a statistically insignificant coefficient does not necessarily mean that the characteristic of interest does not influence price response. It may simply mean that there is insufficient variation in the presence or absence of that particular characteristic in the experimental sample to precisely determine causality. Ensuring that there is sufficient variation in the sample to precisely measure the impact of all variables of interest would have required a much larger sample and a much more expensive experiment than the SPP. In order to maximize the variation in each characteristic, the analysis was done using data pooled across climate zones, as there is often more variation in certain characteristics across zones (e.g., air conditioning ownership, pool ownership, etc.) than there is within a specific climate zone.

The influence of each customer characteristic was examined individually. That is, we did not estimate a model that included all of the variables at once. Since many of these variables are correlated, including all of the variables in a single regression would make

[74] This variable is the same one that was used for sample stratification as discussed in Section 2. The variable equals 1 if a single family household in a climate zone exceeds the high user threshold, 0 otherwise. The threshold varies by climate zone. Only single-family households were stratified. Thus, all multi-family households are characterized as low users, regardless of whether or not their average use exceeds the threshold. The vast majority of multi-family households do not exceed the high user threshold.

it difficult to isolate the specific impact of each variable.[75] On the other hand, examining them one at a time means that the impact of each variable may be overstated in terms of the influence of that particular factor, as the variable is actually a proxy not only for the factor it represents but also for other factors with which it is correlated. This may be irrelevant from a policy perspective, however. Indeed, the combined impact may be exactly what is needed, since few policies are likely to vary across all of the many market segments that might be partially represented by each individual variable. For example, the coefficient on the high user variable may represent the combined impact of higher income, more air conditioning ownership, more pool ownership and perhaps other factors. But since policies are more likely to be targeted at all high users than to high users who do and don't have an air conditioner or who do and don't have a swimming pool, knowing how impacts vary across these sub-segments of high users is irrelevant.

Of the eleven characteristics examined, spa ownership, electric cooking ownership and persons per household were not statistically significant at the 90 or 95 percent confidence levels in the energy share equation of the CES specification. All of the remaining variables except swimming pool ownership were statistically significant at the 95 percent confidence level, with t-statistics ranging from a low of –2.9 for average daily usage to a high of –5.7 for income. Swimming pool ownership, with a t-statistic equal to –1.8, was significant at the 90 percent confidence level.

Table 5-8 shows how the elasticity of substitution varies with each of the remaining variables and Table 5-9 shows the variation in peak-period energy use on CPP days across customer characteristics. Recall from Section 4 that the impact estimates for each rate period are derived from both the share equation (represented by the elasticity of substitution) and the price elasticity of daily energy use. Depending upon the value of the daily price elasticity, the difference in impacts across customers with varying characteristics may be more or less than the difference in the elasticity of substitution. Key findings include:

- The differential impact of central air conditioning ownership on peak-period energy use is quite small. On a statewide basis, households with central air conditioning reduce load by 12.8 percent and those without air conditioning reduce load by 12.3 percent. This overall impact is the result of two countervailing factors. The elasticity of substitution is actually 50 percent higher for households with air conditioning compared to those that don't have air conditioning. However, the price elasticity of daily energy use is actually smaller for households with air conditioning than for households that don't have air conditioning. The net effect is close to zero.[76]

[75] Appendix 9 shows the correlations between the variables tested.
[76] The t-statistic on the interaction term between air conditioning ownership and the price ratio in the share equation is –3.3 and the t-statistic on the daily price/air conditioning ownership term in the daily equation is +3.1. Thus, both variables are highly significant but have opposite influences on the impact estimate, resulting in differences that are quite small.

- High users are significantly more price responsive than low users. For households that use twice the statewide average energy consumption, the reduction in peak-period demand on CPP days is 17.22 percent whereas households that use half the statewide average amount of energy reduce peak-period energy use by only 9.70 percent, a difference of nearly 75 percent. The same general pattern is seen using the high user binary variable.

- High income households are more price responsive than low income households. The reduction in peak-period energy use is 25 percent higher for households with an annual income of $100,000 than for households with an annual income of $40,000.

- Single family households are more price responsive than multi-family households, with single family households showing 37 percent more reduction in peak-period energy use than multi-family households.

- Households living in larger homes are more price responsive than households living in smaller homes. A typical household with a four bedroom home reduces peak-period energy use on CPP days by 14.5 percent whereas a household living in a two bedroom home reduces energy use by only 11.5 percent.

- The reduction in peak-period energy use for households with swimming pools is almost 60 percent greater than for households without swimming pools.

- Households in which the head is a college graduate are more price responsive than households where the head did not graduate from college. The difference in peak-period energy reduction is roughly 23 percent.

Table 5-8
Variation in the Elasticity of Substitution
Given a Change in Customer Characteristics

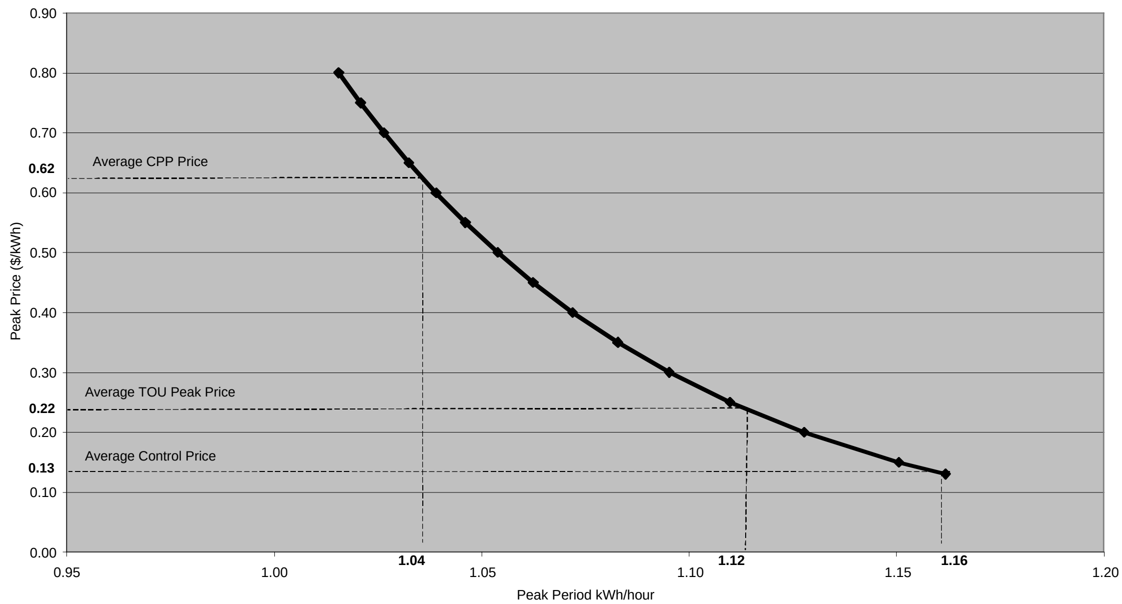
Variable	Customer Characteristic	Zone 1	Zone 2	Zone 3	Zone 4	All
None	Average	-.045	-.061	-.099	-.121	-.077
Central A/C	Yes	-.075	-.083	-.110	-.130	-.095
	No	-.043	-.051	-.078	-.098	-.063
Average Daily Use	200% of Average	-.063	-.080	-.123	-.156	-.099
	50% of Average	-.037	-.050	-.086	-.109	-.065
High User Dummy	High	-.074	-.089	-.125	-.146	-.104
	Low	-.039	-.053	-.089	-.111	-.068
Annual Income	$40,000	-.042	-.057	-.095	-.117	-.073
	$100,000	-.072	-.087	-.125	-.147	-.103
Housing Type	Single Family	-.054	-.069	-.106	-.127	-.085
	Multi-Family	-.028	-.043	-.079	-.101	-.058
# Bedrooms	Two	-.034	-.047	-.081	-.103	-.061
	Four	-.077	-.090	-.125	-.146	-.105
Swimming Pool	Yes	-.076	-.091	-.129	-.151	-.106
	No	-.045	-.060	-.098	-.120	-.076
College Education	Graduate	-.069	-.085	-.123	-.146	-.101
	Did Not Graduate	-.029	-.044	-.082	-.105	-.060

Table 5-9 Variation in the Percent Impact on Peak Period Energy Use on CPP Days Given a Change in Customer Characteristics						
Variable	**Customer Characteristic**	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 4**	**All**
None	**Average**	-8.35	-9.61	-13.37	-17.13	-12.46
Central A/C	**Yes**	-9.92	-10.34	-13.45	-17.19	-12.84
	No	-8.25	-9.32	-13.23	-16.99	-12.27
Average Daily Use	**200% of Average**	-12.13	-13.40	-18.26	-23.78	-17.22
	50% of Average	-6.57	-7.36	-10.35	-14.21	-9.79
High User Dummy	**High**	-11.54	-12.30	-15.62	-19.55	-14.94
	Low	-7.77	-9.02	-12.85	-16.86	-11.95
Annual Income	**$40,000**	-7.99	-9.24	-12.98	-16.56	-12.05
	$100,000	-11.61	-12.52	-15.92	-19.43	-15.13
Housing Type	**Single Family**	-9.77	-10.81	-14.27	-17.94	-13.47
	Multi-Family	-5.74	-7.03	-10.66	-14.41	-9.80
# Bedrooms	**Two**	-7.44	-8.67	-12.42	-16.19	-11.52
	Four	-11.49	-12.06	-15.10	-18.80	-14.50
Swimming Pool	**Yes**	-15.37	-16.48	-20.19	-23.53	-19.23
	No	-8.41	-9.52	-12.97	-16.45	-12.14
College Education	**Graduate**	-10.67	-11.53	-14.88	-18.52	-14.13
	Did Not Graduate	-7.00	-8.49	-12.55	-16.24	-11.49

5.1.4 DEMAND CURVES FOR THE CPP-F RATE

One way to illustrate the performance of the demand model is to derive and plot its demand curves. The demand curve in Figure 5-1 shows how energy use in the peak period varies with peak period price, other things equal. The curve shows the combined impact of the elasticity of substitution and the daily price elasticity of demand. The curve shows the combined impact of the elasticity of substitution and the daily price elasticity of demand. It should be noted that a number of factors are held constant along the curve. If any of these factors change, such as weather , the saturation of air conditioning or off-peak prices, the curve will shift to the left or right, depending upon the nature of the change in the underlying factors. The curve will shift to the right, for example, as the weather heats up.

Figure 5-1
Peak Period Demand Curve, Statewide



The demand curve shows that at a price of 13 cents/kWh, which is the approximate price facing the control group and the price that the treatment customers faced in the pre-treatment period, electricity use is 1.16 kWh/hour during the peak period. At a price of 22 cents/kWh, corresponding to the average TOU peak-period price, demand falls to 1.12 kWh/hr. Thus, a rise in the price of 69.23% produces a drop in electricity use of 3.45%, yielding an implicit arc own-price elasticity of demand of -0.050 (= -3.45%/+69.23%). When the price increases to 62 cents/kWh, corresponding to the average CPP peak-period price on CPP days, demand falls to 1.04 kWh/hr. Thus, a rise in the price of 377% from the initial value of 13 cents/kWh produces a drop in electricity use of 10%, yielding an implicit arc own-price elasticity of demand of –0.027. The arc elasticity falls with rising prices, indicating the non-linear nature of price responsiveness.

Figure 5-2 shows the demand curve for off-peak electricity use. It shows that a reduction in the price of off-peak electricity from the control group value of 13 cents/kWh to 9 cents/kWh for a TOU rate increases hourly energy use from 0.759 kWh to 0.772 kWh. That is, a 31 percent decrease in price induces a rise in demand of 2%, yielding an implicit arc own-price elasticity of off-peak demand of -0.05, very similar to the value observed for peak period usage for a TOU rate.

Figure 5-2
Off-Peak Period Demand Curve, Statewide

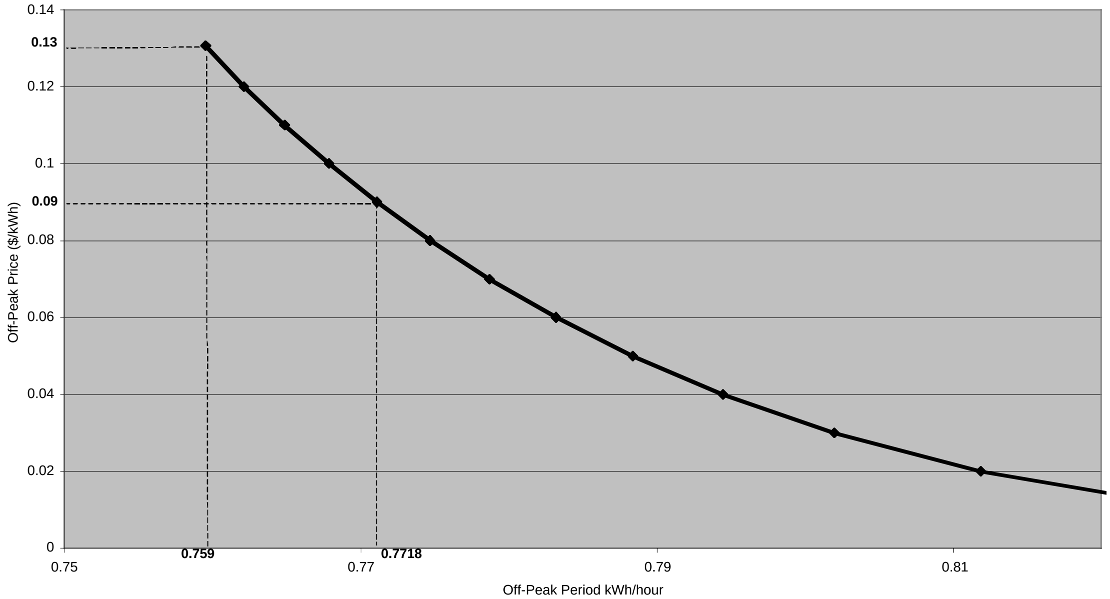


Figure 5-3 shows the influence of central air-conditioning on the demand curve for peak-period electricity use. The demand curve for customers with central air-conditioning has a slightly steeper slope than the average statewide demand curve, indicating a lower degree of price responsiveness. While this may seem counterintuitive at first, it reflects the net effect of two countervailing factors. The peak/off-peak ES is higher for customers with CAC (-0.095 versus –0.063 for customers with no CAC) but the daily price elasticity is lower (+0.01 versus –0.05). The net effect is a lower price response for customers with CAC. The demand curve for customers with no central air conditioning has a slightly flatter slope, indicating slightly higher price response.

Figure 5-3
Peak Period Demand Curves, Default and CAC Variations, Statewide

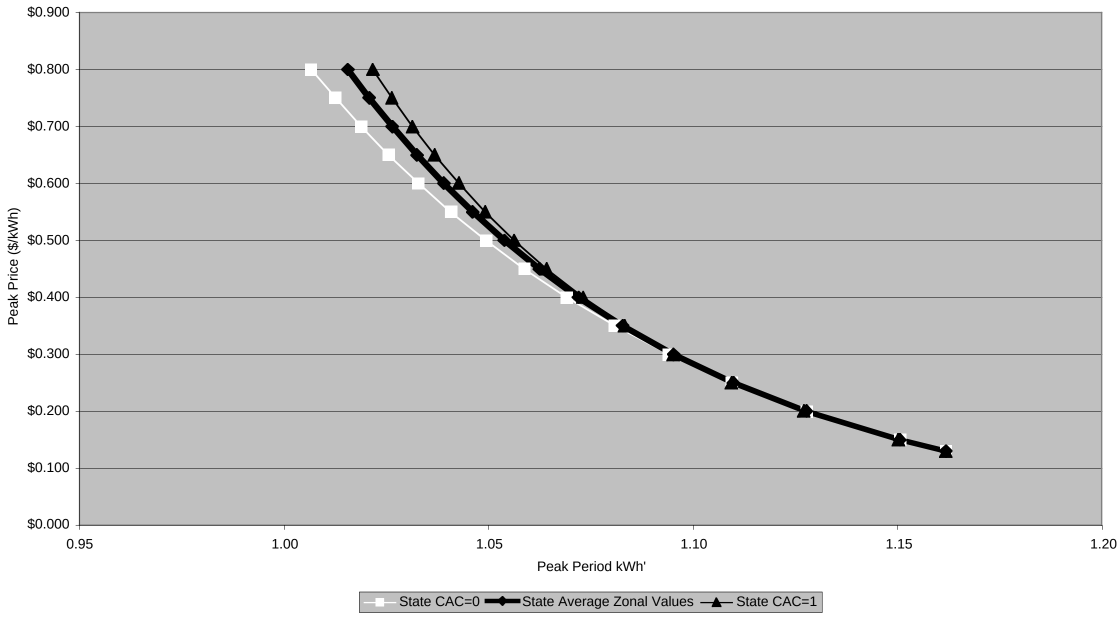
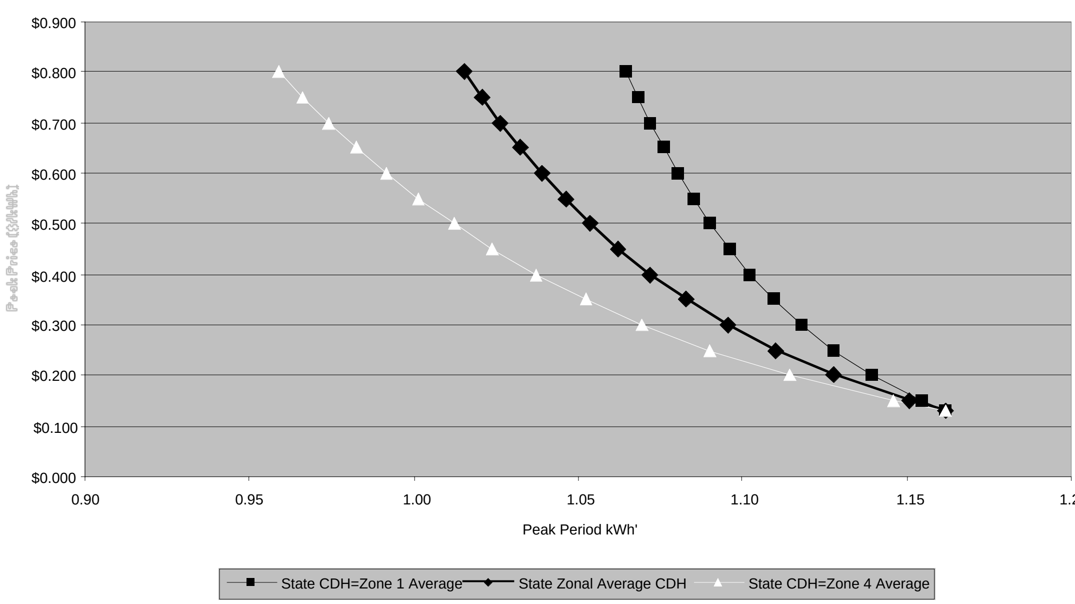


Figure 5-4 shows the influence of weather on the slope of the demand curve. Hotter weather conditions produce a flatter, more price-responsive demand curve, and cooler weather conditions produce a steeper, less-price responsive demand curve.

Figure 5-4
Peak Period Demand Curves, Default and Weather Variations, Statewide



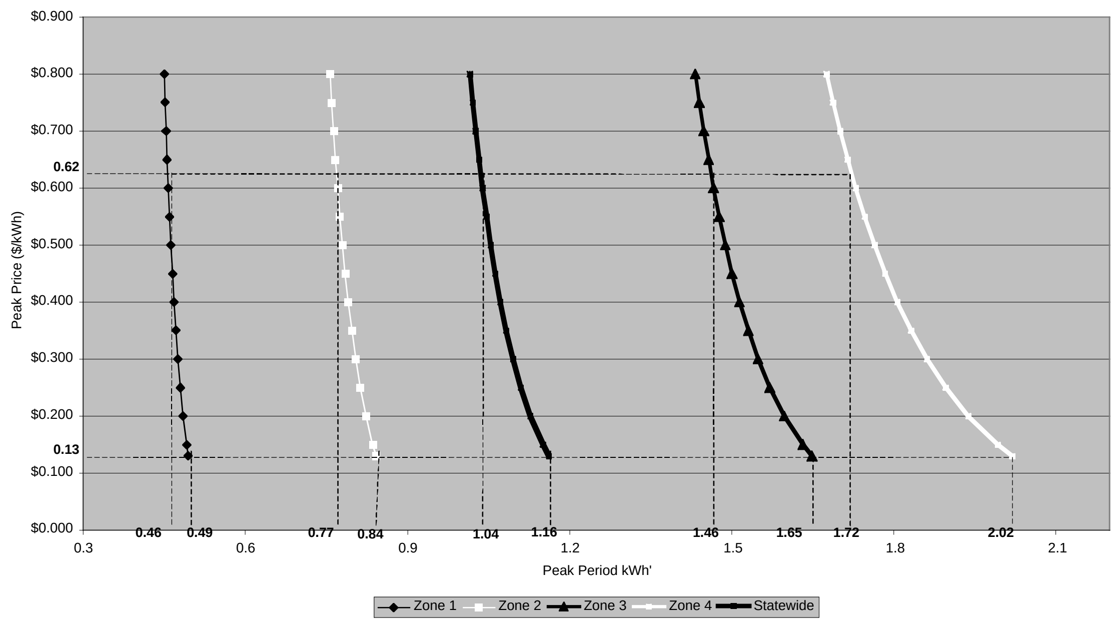
5. Residential Demand Models and Impact Estimates

Similar demand curves can be constructed for peak and off-peak energy use in each of the four climate zones. The demand curves would be expected to vary across zones, because weather conditions and the saturation of central air conditioning vary by zones, and this causes variation in the ES and in the daily price elasticity of demand. Values for these variables and parameters were reported earlier in Table 2.

Based on these values, the steepest demand curve (showing the least amount of price responsiveness, as evidenced by an ES of -0.03 and a daily price elasticity of –0.04) will be found in Zone 1, and the flattest one (showing the highest amount of price responsiveness, as evidenced by an ES of –0.11 and a daily price elasticity of –0.03) in Zone 4.

Figure 5-5 displays demand curves for each of the four zones, and also repeats the statewide demand curve for comparison. It shows how much the quantity consumed in the peak period would change by zone as the price of electricity moves up from 13 cents/kWh to 35 cents/kWh. The biggest impact is observed in Zone 4 (-8.46%), followed by Zone 3 (-6.67%), Zone 2 (-4.76%) and Zone 1 (-2.04%). The implied arc elasticities of demand are -0.05 in Zone 4, -0.04 in Zone 3, -0.03 in Zone 2 and –0.01 in Zone 1.

Figure 5-5
Peak Period Demand Curves by Zone



5.1.5 Weekend/Holiday Analysis

All of the results presented in sections 5.1.1 through 5.1.4 pertain to weekday energy use. This section examines energy use on weekends and holidays (abbreviated as weekend/holidays henceforth). It is important to note that all energy during weekends and holidays is priced at off-peak rates. Table 5-10 presents estimates of mean electricity use per hour for control and treatment customers for selected time periods. A comparison of weekday and weekend/holiday energy use per hour for control customers indicates that customers use between 23 and 34 percent more electricity on weekends/holidays than on weekdays.

Table 5-10
Average Energy Use Per Hour

Group	Day Type	Time Period	Zone 1	Zone 2	Zone 3	Zone 4
Control	Weekday	Pretreatment	.41	.58	.80	1.07
		Treatment	.45	.60	.84	1.14
	Weekend/Holiday	Pretreatment	.51	.77	1.03	1.43
		Treatment	.58	.88	1.26	1.53
CPP-F	Weekend	Pretreatment	.53	.76	1.01	1.38
		Treatment	.61	.87	1.18	1.42
TOU	Weekend/Holiday	Pretreatment	.56	.81	1.01	1.51
		Treatment	.56	.84	1.27	1.58

In general, energy use for control and treatment customers is reasonably similar in the pretreatment period, although the differences are larger for TOU than for CPP-F customers. For CPP-F customers, the difference in weekend/holiday energy use between treatment and control customers in the pretreatment period is small, ranging from a low of –1 percent in zone 3 to a high of +3.7 percent in zone 1. The differences are somewhat larger when comparing control and treatment customers for the TOU rate, where zone 1 treatment customers use almost 10 percent more energy on average than do control customers in the pretreatment period. The differences in zone 2 and 4 are roughly +5 percent, whereas the difference in zone 3 is –1.6 percent.

Two primary questions are addressed in this section. The first concerns whether there is any evidence of load shifting from the weekday peak period or weekdays in general to weekends/holidays. The second concerns whether consumers respond to price signals on weekends/holidays and, if so, what are their price elasticities. Both of these questions are important in answering the general policy question concerning whether time-varying rates increase, decrease or leave unchanged total annual energy use.

The first question is addressed in two ways. First, we ran the double-log demand model for the off-peak energy equation using weekend data only. The specification included both peak-period and off-peak period prices as explanatory variables. A positive, statistically significant coefficient on the peak-period price term would represent evidence of load shifting from the weekday peak period to the weekend/holiday period.

A second approach used the CES energy share equation to examine whether there is any evidence of a shift in daily energy use from weekdays to weekends/holidays. With this specification, the left-hand-side regression variable is the ratio of weekday, daily energy use per hour (i.e., based on the sum of peak and off-peak use during weekdays) to weekend/holiday daily energy use per hour and the right-hand-side price term is the ratio of average daily price during weekdays to average daily price on weekends. A negative, statistically significant coefficient on the price term would represent evidence that consumers are shifting energy use from weekdays, when average prices are higher, to weekends/holidays, when prices are lower.

With regard to the first approach, the analysis used a 2-observation database consisting of average values for pretreatment and treatment-period weekends/holidays. As previously mentioned, a significant and positive coefficient on the peak-period price would indicate that customers are shifting load from the peak-period on weekdays to weekends. The analysis shows that none of the peak-period price terms in the demand models are statistically significant. Indeed, the highest t-statistic for the CPP-F rate is only –0.94 and the highest for the TOU rate is only –0.84. That is, there is no evidence of shifting from weekday peak periods to weekends/holidays.

With regard to the second approach (e.g., using the CES energy share equation, where the dependent variable is the ratio of average weekday energy use per hour to average weekend energy use per hour), none of the t-statistics on the price ratio term are statistically significant for the CPP-F treatment group. They range from a low of –0.25 in zone 1 to a high of –1.23 in zone 3. The value of the coefficients are quite small, ranging from +.01 in zone 4 to -.04 in zone 3. Oddly, the coefficients and t-statistics for the TOU rate are much larger. Indeed, the coefficient on the price ratio in zone 2 equals -.25 and is statistically significant with a t-statistic equal to –2.1. However, we do not consider these results to be credible. The average CPP-F weekday price is higher than the average TOU weekday price and, therefore, should elicit more switching if any switching is occurring. Furthermore, there is an inconsistency in these results for the TOU rate with the results reported in the previous paragraph. Therefore, we do not consider these anomalous results for the TOU rate as credible evidence of any significant shifting between weekdays and weekends/holidays. In summary, neither test showed any evidence of load shifting from weekdays to weekends/holidays.

Next, we turn to the issue of price response on the weekend. To estimate price elasticities on the weekend, we developed a 10-observation dataset, based on the concept of quintiles, after initial regressions using the 2-observationi database showed no statistically significant price response on weekends. The quintile concept was used in the weekday analysis as well, where it yielded a 15-observation dataset. Consecutive Saturday and Sunday observations (as well as contiguous holidays) were averaged to create a single average weekend observation for each unique weekend in both the pretreatment and treatment periods. System-wide load quintiles were created similarly by ranking the averaged system-wide daily peak load on consecutive weekend days. In both time periods, observations within each load quintile were averaged to create a dataset consisting of 5 pretreatment observations and 5 treatment observations for each customer, collectively known as the 10-observation dataset.

The weekend price elasticities were estimated using the double-log specification. The specification regressed the log of off-peak energy use (entire daily use for a weekend/holiday observation) on the log of the off-peak price, weather, CAC ownership, and price interaction terms with weather and CAC. The model was estimated using data pooled across the four climate zones.

Estimation of the pooled model with interactions between the price term and weather and CAC yielded a negative coefficient on the interaction term between CAC and price. The coefficient had a value of –0.227 with a t-statistic of –5.314. Combining this coefficient with the coefficient on the interaction term on price and weather and with the coefficient on the price term by itself yields an effective own-price elasticity on weekend/holiday use of –0.067 for the state as a whole. The values by zone are as follows: zone 1 is –0.001, zone 2 is –0.046, zone 3 –0.116 and zone 4 is –0.099. Table 5-11 shows the impact of the lower off-peak price on weekend energy use using this approach.

Table 5-11
Weekend/Holiday Impact Estimates For SPP Rates

Climate Zone	Base Use (kWh/hr)	Change in Use (kWh/hr)	Percent Change in Energy Use
1	0.58	+0.00	+0.04%
2	0.88	+0.01	+1.56%
3	1.26	+0.06	+4.41%
4	1.53	+0.06	+4.05%
All	1.02	+0.03	+2.89%

5.2 TOU RATE ANALYSIS

This section examines the impact of the residential TOU rate on energy use by rate period. Before discussing the results, it is useful to recall the purpose of the TOU treatment cells in the design of the SPP. The CPP-F rate tariff consists of a TOU rate that differs on CPP and non-CPP days. As such, the CPP-F rate can be used to estimate response to both the very high CPP rates on CPP days as well as the more moderate TOU rates on non-CPP days. However, in the early design stages of the SPP, some felt that it would be useful to have a pure TOU treatment to allow for comparisons with other studies. Since there was a fixed budget for conducting the SPP, the bulk of it was devoted to populating the CPP-F treatment cells, given that there was greater uncertainty about customer response to CPP-F rates than to TOU rates and greater potential benefits that might be achievable from these dynamic rates. Consequently, the final sample design allocated only 57 customers on average to each TOU treatment cell versus 161 customers on average for each climate zone for the CPP-F rate. As seen later in this section, we believe the small TOU sample sizes have contributed to the odd results discussed below for the TOU rate treatment.

We have analyzed the impact of TOU customers with reference to the same control groups that were used to analyze the impact of CPP-F customers. The analysis was performed with averaged data, using both a 2-observation database (one observation for each customer representing the pre-treatment period and one representing all weekdays in the treatment period) and a 10-observation database consisting of five load quintiles each in the pretreatment and treatment periods. This database is similar to the 15-observation database used for the CPP-F analysis discussed previously but it combines CPP and non-CPP days.

Both the double-log and CES model specifications were used in the estimation of demand models. The results are shown in Table 5-13 for the double-log model and in Table 5-13 for the CES model. Table 5-13 also contains estimates of the elasticity of substitution based on the CPP-F treatment and represents the first step in comparing results between the two treatment groups.

As seen in Table 5-12, using the 2-observation data set with the DL model, we find that none of the eight own-price and cross-price elasticities of demand for the TOU rate are statistically significant at the 95% level.[77] The own-price elasticity for zone 3 is significant at the 90% level. However, the level of statistical significance improves when the 10-observation database is used. Three of the eight elasticities are statistically significant with this database, including the two own-price elasticities for peak and off-peak electricity use for zone 3 and the own-price elasticity for off-peak electricity use for zone 1.

Table 5-12
Own-Price and Cross-Price Elasticities of Demand
Double-Log Model

Climate Zone	Price	Two-Observation		Ten-Observation	
		Peak Usage	Off-Peak Usage	Peak Usage	Off-Peak Usage
1	Peak	+0.01	-0.09	+0.09	-0.03
	Off-Peak	-0.08	-0.27	-0.07	**-0.24**
2	Peak	-0.03	-0.00	-0.05	-0.07
	Off-Peak	+0.27	-0.06	+0.19	-0.11
3	Peak	*-0.30*	+0.07	**-0.32**	0.02
	Off-Peak	0.01	-0.11	0.07	**-0.20**
4	Peak	+0.02	+0.06	-0.03	-0.00
	Off-Peak	+0.03	-0.00	-0.08	-0.04

[77] Values in bold in each table represent variables that are significant at the 95 percent confidence level. Values in italics represent variables that are significant at the 90 percent confidence level.

With the CES demand model, the elasticity of substitution based on the 2-observation database is statistically significant in zones 2 and 3 and insignificant in the other two zones. While the absence of response in the cool climate of zone 1 is not surprising and is consistent with results obtained from the CPP-F rate, the absence of response in the hot climate of zone 4 is inconsistent with expectations and with the CPP-F findings.

To better understand the relationship between the findings from the TOU and CPP-F samples, we conducted several explorations with alternative data sets. The first is summarized in Table 5-13, which compares the elasticity of substitution based on the TOU and CPP-F databases. As seen, there are large differences in the elasticities in zones 2, 3 and 4 for both the 2 observation and 10 observation databases.

Table 5-13
Elasticity of Substitution
TOU and CPP-F Customers on Non-CPP Days
CES Model

Climate Zone	2-Observation		10-observation	
	TOU	CPP-F	TOU	CPP-F
1	-0.01	-0.06	+0.02	-0.03
2	**-0.12**	-0.02	**-0.07**	-0.01
3	**-0.25**	**-0.13**	**-0.27**	**-0.12**
4	-0.03	**-0.14**	-0.02	**-0.13**

Next we estimated models based on data pooled across climate zones using both the 2-observation and the 10-observation databases. The results using the 2-observation database indicate that zonal dummies are significant in Zones 2 and 3, which is consistent with the findings from the individual zonal analysis reported above. Introduction of a CAC interaction term yielded a positive sign on the coefficient that was statistically significant. This finding is inconsistent with the results based on the CPP-F treatment customers as well as findings in the literature, which show that consumers with central air conditioning have higher elasticities of substitution than do customers without central air conditioning. The CAC interaction term also failed to diminish the statistical significance of the zonal dummies for zones 2 and 3. They remained strongly significant. Finally, when we introduced a weather interaction term, it had the correct sign (it was negative) but was not significant.

Next, we pooled the TOU and CPP-F (non CPP days) data and included a binary variable representing TOU customers as an interaction variable with the price term. Separate regressions were run for each climate zone. The results are displayed in Table 5-14. The interaction term was insignificant in zones 1 and 2 and significant in zones 3 and 4 with the 2-observation database. Using the 10-observation database, the TOU/price interaction term was significant in all climate zones.

Table 5-14 Pooling TOU and CPP-F customers Coefficient on TOU Binary Variable and Price Interaction Term		
Climate Zone	**2-Observation**	**10-Observation**
1	+0.06	**+0.05**
2	-0.06	**-0.05**
3	**-0.13**	**-0.13**
4	**+0.12**	**+0.11**

There is very little numerical difference in the value of the binary coefficient based on the 2-observation and 10-observation databases. The analysis indicates that TOU customers have a higher elasticity of substitution than do CPP-F customers in zone 2 (-0.06 versus –0.01), a much higher one in Zone 3 (-0.26 versus –0.13), a much lower elasticity of substitution in zone 4 (-0.02 versus –0.13) and a somewhat lower value in zone 1 (+0.02 versus –0.03).

Next, we explored the difference in results between the TOU and CPP samples by reviewing the load shape graphs for customers on the low ratio TOU rate separately from those on the high ratio TOU rate. Nothing unusual surfaced in zones 1, 2 and 3. However, in zone 4, it was apparent that customers on the low ratio rate had a marked dip in usage during the peak period while those on the high ratio rate actually had a marked rise during the peak period. Consequently, we reran the CES demand model for zone 4 and included a binary variable for the high ratio customers. This binary variable was interacted with the price ratio term. It was found to be significant, confirming that the two sets of customers are behaving differently.

The elasticity of substitution for the low ratio customers was –0.16 and was statistically significant at the 95% level. The implied elasticity of substitution for the high ratio customers was +0.13. While it's not clear why customers in the high ratio group are increasing electricity use during the expensive peak period, the result is economically irrational and including these customers in the analysis negates the more rational response of the low-ratio treatment group.

In summary, models estimated using the TOU treatment data were generally not credible, due perhaps to the much smaller samples that were drawn for the TOU rate treatment. Based on the detailed analysis summarized above, we recommend that the CPP-F demand models be used to predict the impact of TOU rates. Table 5-15 summarizes the TOU impact estimates. The overall reduction in peak-period energy use is just over 4 percent. This compares with a reduction of more than 12 percent for the CPP-F rate. Off-peak energy use increases by less than 2 percent and daily energy use changes only slightly. The overall increase in energy use across weekdays and weekends resulting from the SPP TOU rates is 0.75 percent.

Table 5-15
Impact Estimates For Average TOU SPP Tariff

Climate Zone	Impact Measure	Peak	Off-Peak	Daily	Weekend	Average Summer Day
Zone 1	Base Use (kWh/hr)	0.49	0.46	0.46	0.58	0.50
	Change (kWh/hr)	-0.01	0.00	0.00	0.00	0.00
	% Change	-1.76	0.79	0.23	0.03	0.16
Zone 2	Base Use (kWh/hr)	0.79	0.61	0.65	0.88	0.72
	Change (kWh/hr)	-0.02	0.01	0.00	0.01	0.00
	% Change	-2.82	1.18	0.16	1.14	0.52
Zone 3	Base Use (kWh/hr)	1.48	0.89	1.01	1.26	1.08
	Change (kWh/hr)	-0.07	0.02	0.00	0.04	0.01
	% Change	-4.84	2.21	0.06	2.97	1.08
Zone 4	Base Use (kWh/hr)	1.82	1.07	1.23	1.53	1.32
	Change (kWh/hr)	-0.11	0.03	0.00	0.03	0.01
	% Change	-5.86	2.72	0.07	2.28	0.84
All Zones	Base Use (kWh/hr)	1.06	0.72	0.79	1.02	0.86
	Change (kWh/hr)	-0.04	0.01	0.00	0.02	0.01
	% Change	-4.12	1.76	0.11	1.91	0.75

5.3 CPP-V RATE ANALYSIS

In addition to the CPP-F and TOU tariffs summarized above, the SPP also tested a CPP-V tariff. This tariff has a variable-length CPP period with shorter lead times for notification of CPP events. In addition, each customer has a smart thermostat that automatically adjusts the air conditioner during CPP events. This treatment was tested in the San Diego service territory only and participants are primarily located in climate zone 3 in San Diego, which tends to be a bit milder than the statewide climate zone 3. All consumers on this tariff have central air conditioning and live in single family households with usage above 600 kWh per month. Both treatment customers and the control group with which they are compared had previously volunteered to be in the AB970 Smart Thermostat pilot. Thus, the results from this treatment are not directly comparable to those for the CPP-F tariff and they cannot be generalized to the population at large.

The estimating database consists of 15 observations for each customer, with each observation representing the average energy use for days that are distinguished by treatment-pretreatment time period, non-CPP and CPP day type within the treatment period, and system-load conditions sorted into quintiles. The demand models summarized here are derived using data for a control group that has enabling technology, but for which the technology was not dispatched on the same days as for the treatment group. Thus, the price elasticities and impact estimates represent the combined impact of the enabling technology and price-induced behavioral changes over and above the impact of the technology. These behavioral changes might involve adjusting the thermostat over and above what is done automatically, shifting laundry or cooking to off-peak periods, adjusting the timing of pool pump usage, reducing lighting levels, turning off fans, or other actions.

Twelve CPP days were called during the summer of 2003. On six days, the enabling technology was dispatched for two hours and on the remaining six days, it was dispatched for the entire five-hour peak period. Table 2-1 in section 2 lists the CPP days and the length of the dispatch period for each day.

The San Diego climate in which SPP participants are located is a hybrid of the statewide climate zones 2 and 3. Peak-period degree hours per hour in the San Diego area are closest to those of statewide climate zone 2. On non-CPP days, the San Diego peak-period value is about 5 percent higher than that of the statewide climate zone 2. On CPP days, the difference is roughly 7 percent. During the off-peak period, however, the San Diego climate is closer to that of statewide climate zone 3. The number of cooling degree hours in the off-peak period in San Diego is nearly three times that of climate zone 2 but the number is about 14 percent less than that of climate zone 3. On a daily basis, the San Diego climate, with cooling degree hours per hour equal to 2.8 on non-CPP days, is in between the statewide zone 2 and zone 3 values of 1.7 and 4.3.

When estimating the demand models, an interaction term between price and a binary variable equal to 1 on CPP days was used to test whether price responsiveness varies between CPP and non-CPP days. Unlike the results obtained for the CPP-F rate, which generally showed no statistically significant differences between CPP and non-CPP days, the interaction variables for the CPP-V rate are highly significant in both the CES and double-log formulations. This is not surprising given the presence of the enabling technology that is dispatched only on CPP days.

For the CES specification, the coefficient on the interaction term in the energy share equation equals –0.148 with a t-statistic equal to –6.4. The variable is also statistically significant at the 95 percent level in the daily energy use equation. For the double-log specification, three of the four interaction terms are statistically significant at the 95 percent level and the fourth is significant at the 90 percent level. In short, for the CPP-V rate, price responsiveness is clearly greater on CPP days than it is on non-CPP days.

The impact of weather on price responsiveness was also examined. For the CES specification, the weather/price interaction terms are significant at the 95 percent level in both the energy share and daily demand models (with t-statistics equal to –8.2 and –2.3 respectively). Both equations show responsiveness increasing as cooling degree hours increase. For the double-log specification, the interaction terms for the peak energy use equation are highly significant, with the t-statistic for the own-price interaction term equal to –9.6 and the t-statistic for the cross-price term equal to –2.7. For the off-peak energy demand equation, the own-price interaction term is not statistically significant but the cross-price interaction term is.

Table 5-16 shows the estimated values for the elasticity of substitution and the daily price elasticity for various day-types and weather combinations. Tables 5-17 and 5-18 contain similar information for the own- and cross-price elasticities based on the double-log specification. The cooling degree hour values shown in each table represent the average values for each variable for the control group during weekdays in the Summer 2003 period overall as well as the values that represent the days in each of the five system-load quintiles. It is important to note, however, that we have presented the data in descending order for each cooling degree hour variable rather than in descending order of the highest system load days to the lowest system load days.[78] The San Diego climate differs from the statewide climate and the hottest days in San Diego last summer were actually associated with the fourth statewide system load quintile.

Table 5-16
Elasticity of Substitution and Daily Price Elasticity Based on the CES Specification

Weather (Peak CDH/hr – Off-Peak CDH/hr)		Elasticity of Substitution (ES)		Weather (Daily CDH/hr)		Daily Price Elasticity	
CPP Day	Non-CPP Day	CPP Day	Non-CPP Day	CPP Day	Non-CPP Day	CPP Day	Non-CPP Day
Avg (5.2)	Avg (3.3)	-.20	-.01	Avg (3.2)	Avg (2.8)	-.30	-.26
9.3	5.3	-.30	-.06	6.0	4.5	-.46	-.36
6.1	4.0	-.22	-.03	5.1	3.4	-.41	-.30
4.7	4.2	-.19	-.03	3.3	3.3	-.31	-.29

[78] The results for the CES specification are presented in descending order based on the daily cooling degree hour variable. Daily degree hours and the difference between peak period and off-peak period degree hours do not always move together, which explains the fact that the difference variable does not appear in descending order in Table 4-15.

5.3	1.7	-.21	+.03	2.3	1.9	-.25	-.21
2.0	1.0	-.13	+.04	1.1	1.0	-.18	-.15

Table 5-17
Peak Period Own and Cross-Price Elasticities
Based on the Double Log Specification

Weather (Peak Period CDH/hr)		Own Price Elasticity		Cross Price Elasticity	
CPP Day	Non-CPP Day	CPP Day	Non-CPP Day	CPP Day	Non-CPP Day
Avg (7.4)	Avg (5.4)	-.22	-.04	-.20	-.26
13.7	8.7	-.44	-.15	-.43	-.38
10.0	6.7	-.31	-.08	-.29	-.31
6.9	6.5	-.20	-.08	-.19	-.30
6.6	3.2	-.19	+.04	-.17	-.19
2.8	1.7	-.06	+.09	-.04	-.13

Table 5-18
Off-Peak Period Own and Cross-Price Elasticities
Based on the Double Log Specification

Weather (Off-Peak Period CDH/hr)		Own Price Elasticity		Cross Price Elasticity	
CPP Day	Non-CPP Day	CPP Day	Non-CPP Day	CPP Day	Non-CPP Day
Avg(2.3)	Avg(2.1)	-.02	-.06	+.01	+.09
4.4	3.4	-.08	-.09	-.03	+.07
3.9	2.5	-.06	-.07	-.02	+.08
2.2	2.6	-.02	-.07	+.01	+.08
1.4	1.5	+.00	-.05	+.03	+.10
0.8	0.8	+.01	-.03	+.04	+.04

As seen in the tables, price responsiveness varies significantly on CPP and non-CPP days for customers in the pilot. The reader is reminded once again that these customers do not represent the population as a whole, but rather customers who volunteered for the original Smart Thermostat pilot and volunteered again for the SPP pricing pilot. All of these customers live in single family households, have central air conditioning and also have an enabling technology to automate response on CPP days. Keeping this in mind, the combination of the enabling technology and price-induced response on CPP days results in an elasticity of substitution on CPP days equal to -.20, whereas on non-CPP days, the elasticity of substitution is close to zero. Similar differences are found for the own-price elasticity of demand for peak-period energy use in Table 5-17, with the average CPP-day value equal to -.22 and the non-CPP day value equal to -.04. Differences in the daily price elasticity of demand are much smaller, with the CPP-day value equal to -.30 and the non-CPP day value equal to -.26. There is also much less variation across day-types in the own-price elasticity for off-peak energy use, with the CPP and non-CPP day price elasticities equal to -.02 and -.06, respectively.

The values summarized in the tables also indicate that price responsiveness is greater on hotter days than on cooler days for this group of customers, regardless of day type. On CPP days, the elasticity of substitution is more than twice as large when the difference between peak period and off-peak cooling degree hours equals 9.3 than when the difference equals 2.0.[79] A five-fold increase in average daily cooling degree hours per hour results in roughly an 85 percent increase in the daily price elasticity on CPP days. Roughly a five-fold increase in peak period cooling degree hours leads to more than a seven-fold increase in the own-price elasticity of demand during the peak period on CPP days. The variation in price responsiveness with weather conditions is much less on non-CPP days, when the enabling technology is not operating.

The average reduction in peak-period energy use per hour from the CPP-V tariff on CPP days is 34.5 percent. Off-peak energy use also falls on CPP days, by 6.6 percent. The non-CPP day reductions in peak and off-peak period energy use are much smaller, equaling –2.03 percent and 1.07 percent, respectively. Independent analysis of load shapes carried out by the California Energy Commission suggests that the reduction in peak-period energy use on CPP days attributable to the smart thermostat technology alone amounts to roughly half of the total reduction attributable to the CPP-V rate when it is offered in conjunction with the smart thermostat program. This would suggest that of the total reduction of 34.5 percent cited above, about 17.25 percent is due to the smart thermostat technology by itself and another 17.25 percent due to the behavioral responses triggered by the tariff.[80]

Responsiveness varies with weather for the CPP-V tariff. Based on the weather conditions on the two CPP days that had the highest statewide system load in the summer of 2003, the reduction in peak-period energy use is estimated to equal 39.42 percent. On the two CPP days with the lowest statewide load, the reduction in peak-period energy use was 23.34 percent. However, the two CPP days with the highest statewide system load were not the warmest days in San Diego’s service territory. If the weather for the two days hottest CPP days in San Diego’s is used, the peak-period reduction in energy use is 47.42 percent.

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[79] Recall from section 3 that the weather term used in the CES trade-off equation is the difference in cooling degree hours per hour during the peak and off-peak periods.

[80] The SPP featured three cells for customers on the CPP-V rate. One was a control group with the standard (inverted tier, non time-varying) rate. Another group was on the smart thermostat program but on the standard rate. A third group was on the smart thermostat program and on the CPP-V rate. The analysis carried out by the California Energy Commission found that the second group, when compared with the first, had a drop of 23 percent in peak energy consumption while the third group, when compared with the first, had a drop of 48 percent in peak energy consumption. For additional details, consult Pat McAuliffe and Arthur Rosenfeld, “Response of Residential Customers to Critical Peak Pricing and Time-of-Use Rates During the Summer of 2003,” California Energy Commission, September 23, 2004.

5. Residential Demand Models and Impact Estimates

Figures 5-6 and 5-7 contain estimates of the percentage and absolute impact of the SPP rates as a function of variation in weather conditions. These estimates are based on the CES model. When reviewing the figures, it is important to keep several things in mind. First, these figures represent the average impact of the high-ratio and low-ratio rates that were tested in the SPP. Both the percent and absolute impacts will differ if alternative rates are used as input to the demand models underlying these figures. Second, the point estimates shown along each curve represent the actual weather that occurred during the summer of 2003. Finally, as you move along the curves, not only do the underlying price elasticities and elasticities of substitution vary in accordance with the values in Tables 5-16 through 5-18, but so do the average starting values for energy use. That is, both price responsiveness and the amount of load that can be shifted are higher on hotter days than on cooler days. Consequently, there is an even larger change in energy use between hotter and cooler days than there is in the percentage change in energy use.

Figure 5-6
Percent Reduction In Peak-Period Energy Use Based on Variation In Weather

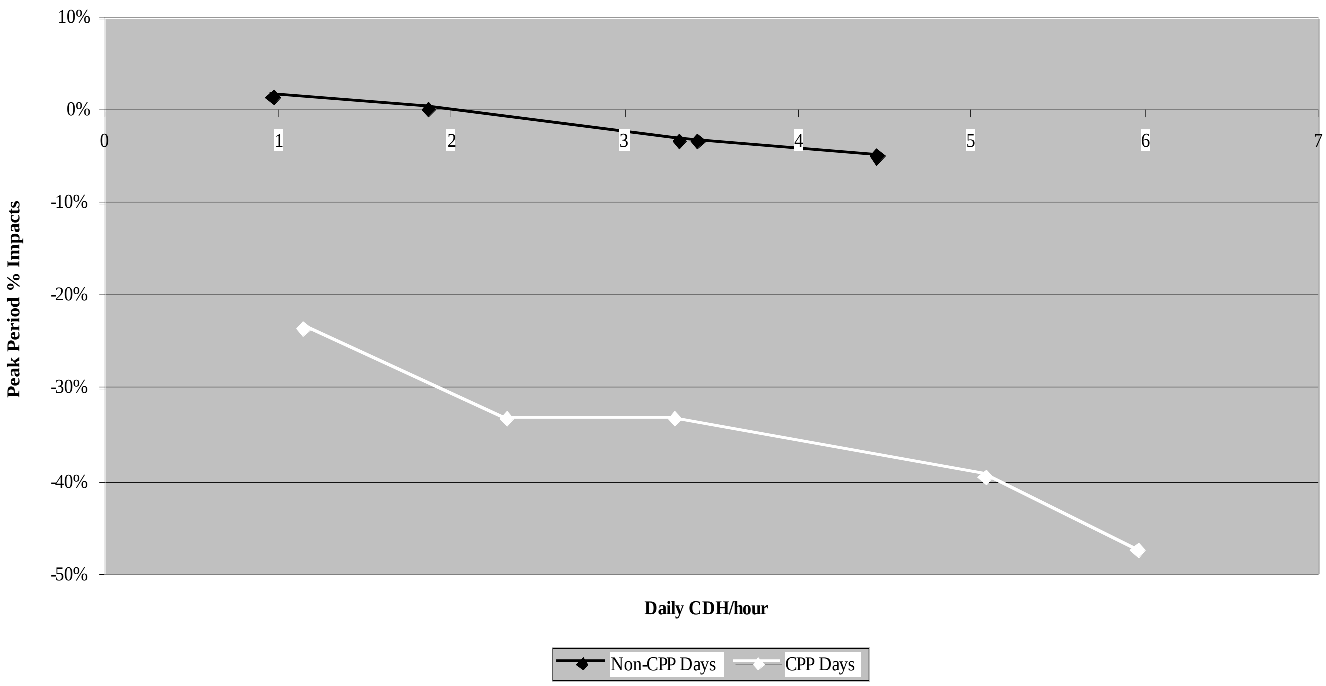
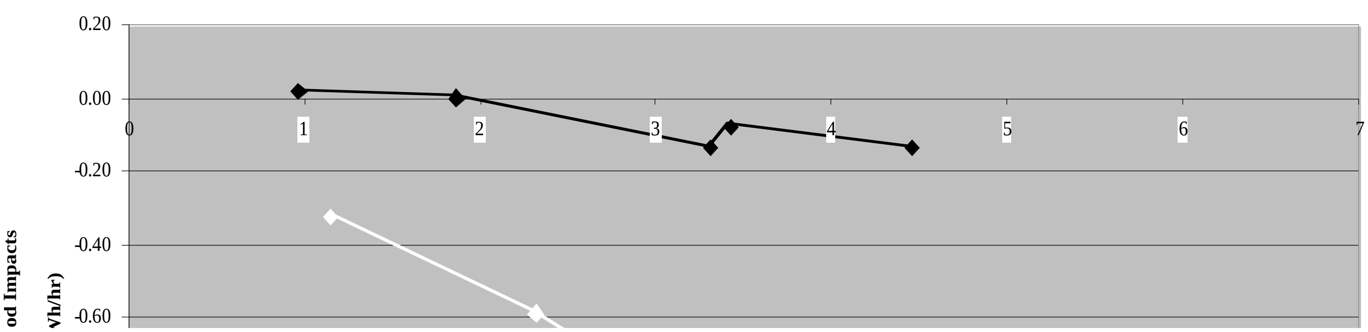


Figure 5-7
Absolute Reduction In Peak-Period Energy Use Based on Variation In Weather



5. Residential Demand Models and Impact Estimates

6. C&I Demand Models and Impact Estimates

This section summarizes the analysis of price responsiveness for C&I customers. The analysis was done separately for C&I customers with peak demands less than 20 kW (LT20) and for those with peak demands between 20 and 200 kW (GT20).

The C&I experiment has examined two rate treatments, a two-period TOU rate and a CPP-V rate consisting of a two-period TOU rate on non-critical days and a three-period rate on CPP days. The normal peak period for both tariffs is from noon to 6 pm except on weekends and holidays when electricity is priced at the off-peak rate during the entire day. On CPP days, customers face the highest price for up to five hours during the peak period. Any time during the noon to 6 pm period on CPP days that is not priced at the critical peak price is priced at the normal peak-period price. Thus, on CPP days, prices vary across three time periods. During the experiment, on six of twelve CPP days, the critical period was for two hours, on five days it was five hours and on one day it covered a four-hour period. The starting times for the critical period varied from one day to the next.[81]

The details and nuances of the C&I sample design are summarized in Section 2.3.2. Briefly, both the control and treatment groups for the TOU rate were drawn from the C&I population as a whole (referred to as Track A customers). Separate samples were drawn for customers with peak demands below 20 kW and for those with peak demands between 20 kW and 200 kW. The CPP-V control and treatment customers were drawn from participants in the AB970 Smart Thermostat pilot program. These customers had volunteered for the AB970 pilot and all have central air conditioning (CAC). They are referred to as Track C customers and do not represent the general C&I population.

As discussed in section 3, the Track C CPP-V customers are quite different than the population as a whole. For example, the LT20 customer segment used roughly 50 percent more electricity on a daily basis than the average customer in this rate class. The GT20 customer segment, on the other hand, shows just the opposite, with treatment customers using 43 percent less electricity on a daily basis than the population at large. Clearly, results from this analysis cannot be generalized to the population as a whole.

For the CPP-V rate, both control and treatment customers have enabling technology as both were chosen from the AB970 Smart Thermostat pilot participants. During the summer of 2003, the enabling technology for both control and treatment customers was dispatched simultaneously on 9 of the 12 CPP days (referred to as common dispatch days) while on two days (differential dispatch days), only the treatment customers' thermostats were dispatched. On the remaining CPP day, both control and treatment customers were dispatched at different times. Thus, on common dispatch days, a comparison of response across control and treatment groups measures the incremental impact of price response over and above the impact derived from the enabling

[81] See Table 2-1 in Section 2 for details about the dates and times associated with each CPP event. Average prices in each time period are shown in Table 3-7

technology. On differential dispatch days, a comparison of control and treatment response measures the aggregate impact of the enabling technology as well as any incremental price response.

6.1 PRICE ELASTICITY ESTIMATES

Each model for CPP-V customers discussed in this section has been estimated using data that has been averaged across the following day types:

- Pretreatment period (June 1 onward)
- Non-CPP days in the treatment period
- CPP days in the treatment period

That is, with the average database, there are three time-series observations for each customer, with treatment customers facing a different price for each time period and control customers facing the same price each time.[82] For the TOU treatment, the database consists of two observations for each customer, one representing average use in the pretreatment period and the other average use across all days in the treatment period.

Before summarizing the price elasticity estimates, it is important to address two issues. The first concerns whether price responsiveness varies across days on which both control and treatment customers were simultaneously dispatched and days on which the treatment group was dispatched but the control group was not. The second concerns whether price elasticities differ on CPP and non-CPP days.

With regard to the issue of common versus differential dispatch days, a priori, one would expect there to be a difference if the majority of price response was produced by the enabling technology used in the CPP-V treatment. If most of the response came from other behavioral factors (e.g., customers setting their thermostats up more than the automated response does, changes in the use of other end uses, etc.), then the difference would be smaller across these dispatch day types. This issue was examined using the CES specification and an interaction term between the price ratio and a binary variable equal to 1 for differential dispatch days, 0 otherwise.

For the LT20 customer segment, the coefficient on the interaction term was quite small (+0.01) and highly insignificant (t = +0.41). That is, there is no statistically significant difference between price response using data from days when the control group was dispatched in the same manner as the treatment group and days when only the treatment group was dispatched. Thus, the two day-types can be pooled.

[82] The analysis reported here was done prior to developing the 15 observation database used for the residential analysis and there was insufficient funding to create the same type of database for the C&I sector. The Summer 2004 analysis may use a more disaggregate approach.

For the GT20 customer segment, the coefficient on the interaction term is also quite small (-0.03) and is marginally significant at the 95 percent confidence level, with a t-statistic equal to 1.96. In spite of the statistical significance, given the small value of the coefficient, we decided to pool the differential dispatch day types, since keeping them separate would not make a material difference in estimated impacts or for any policy decisions.

The second issue of interest is whether price responsiveness varies on CPP and non-CPP days. This issue was also explored using the CES specification and an interaction term between the price ratio and a binary variable equal to 1 for CPP days, 0 otherwise. The model was estimated with all CPP days included (e.g., with both common and differential dispatch days). Surprisingly, the results for the LT20 customer segment show no difference across CPP and non-CPP days, with a coefficient on the interaction term equal to –0.008 and a t-statistic equal to –0.11.

For the GT20 customer segment, the difference across day types is highly significant, but also highly unusual. The coefficient on the day-type/price interaction term equals -0.15 and has a t-statistic equal to –4.24. That is, the elasticity of substitution on CPP days is higher by -0.15 compared to non-CPP days. The unusual part is that the price-ratio term by itself, which represents price responsiveness on non-CPP days, has a positive value equal to +0.11, with a t-statistic equal to 2.60. That is, if these results are to be believed, on non-CPP days, participants increased their peak-period energy use relative to their off-peak period energy use as the ratio of peak prices to off-peak prices increased. This result is inconsistent with economic theory and with other empirical work on the subject. It suggests a potential problem with the GT20 sample that requires further study.

In addition to the specification using the interaction term, for the GT20 customer segment, we also estimated CES models using datasets consisting only of pretreatment and non-CPP day data in one case and pretreatment and CPP-day data in another case. The results were comparable to those based on the specification with the interaction terms. The CPP-day elasticity of substitution is equal to -0.03 and is statistically insignificant, with a t-statistic equal to –1.0. When the data are pooled across non-CPP and CPP days, the elasticity of substitution equals -0.05 and has a t-statistic equal to –3.0.

In light of the anomalous results described above, we do not recommend using the estimated elasticities for the GT20 customer segment for policy analysis at this time. We hope that the addition of the Summer 2004 data will lead to more credible elasticity estimates for this customer segment.

Table 6-1 summarizes the estimated own- and cross-price elasticities, the elasticity of substitution and the daily price elasticities for the CPP-V rate for the LT20 and GT20 customer segments based on the 3-observation database and the CPP-day data pooled across common and differential dispatch days. The LT20 customer segment displays a good deal of price responsiveness, based on either the double-log or CES specification.

The own-price elasticities are around -0.20 for both the peak and off-peak periods and the cross-price elasticities are small. The ES equals –0.15 and the daily price elasticity is –0.13. These values are larger than the elasticities found in the relatively limited literature for this customer segment, and especially large in light of the fact that the control group is dispatched at the same time as the treatment group on most CPP days. This may result from the unique nature of the treatment group, as discussed previously, and these results should not be used to estimate impacts for the general population.

The own price elasticities for the GT20 customer segment are comparable to those for the smaller customers, but the cross-price elasticity of peak-period energy use given a change in the off-peak price is extremely large. The ES is small. As discussed above, we suspect there is some problem here and we do not recommend using these values for policy purposes. Consequently, we have not included any further results in this memo on the GT20 customer segment for the CPP-V rate treatment.

Table 6-1
Price Elasticity Estimates For CPP-V Rate Treatment

Customer Segment	Rate Period	Peak Price	Off-Peak Price	Elasticity of Substitution	Daily Price Elasticity
LT20	**Peak**	**-0.18**	-0.03	**-0.15**	**-0.12**
	Off-Peak	-0.02	**-0.22**		
GT20[83]	**Peak**	**-0.15**	**-0.40**	**-0.05**	**-0.16**
	Off-Peak	-0.02	**-0.21**		

Table 6-2 summarizes the price elasticities for the TOU rate treatment. None of the values are statistically significant. Indeed, the vast majority of coefficients are highly insignificant, with t-statistics in nearly all cases being less than 1.

Table 6-2
TOU Price Elasticity Estimates

Customer Segment	Rate Period	Peak Price	Off-Peak Price	Elasticity of Substitution	Daily Price Elasticity
LT20	**Peak**	+0.02	-0.03	+0.02	-0.19
	Off-Peak	+0.18	-0.03		
GT20	**Peak**	+0.02	-0.03	+0.01	-0.11
	Off-Peak	+0.28	-0.17		

6.2 VARIATION IN PRICE RESPONSE WITH CUSTOMER CHARACTERISTICS

From a policy perspective, it is potentially useful to know if price responsiveness varies with selected customer characteristics. This can be tested by including in the demand

[83] See the discussion in text regarding the recommendation against using the estimates for the GT20 customer segment for policy analysis.

model an interaction term between selected customer characteristics and price. The analysis was done using the CES model specification. The following customer characteristics were examined:

- Size of structure (in thousand square feet)
- Proportion of the total structure that is air conditioned
- Whether or not the building is owner occupied
- The presence of an energy management system
- Number of workers
- Whether of not the structure is a standalone building
- Satisfaction with the utility
- A binary variable representing high usage, as defined by the stratification variable used for developing the sample.

This analysis was performed for the CPP-V treatment and the LT20 customer segment only. Results are summarized in Table 6-3. As seen, the high user binary variable is the only characteristic for which the interaction term is significant at the 95 percent confidence level. The positive sign indicates that larger customers (within this small customer segment) are less price responsive than small customers for this unique group of C&I customers. Indeed, the elasticity of substitution for small users is more than three times larger than it is for larger users. Taken in conjunction with the finding that the elasticity of substitution is virtually zero for the GT20 customers, these results suggest an inverse correlation between price responsiveness and customer size for customers under 200kW load. Since all the customers in the experiment on the CPP-V rate are on a smart thermostat, this result may be a consequence of the smaller role played by CAC in larger customers. The only other statistically significant variable at the 90 percent confidence level is the number of workers, but the coefficient on the interaction term is so small (+.0037) that the impact is negligible.

Table 6-3 Regression Coefficients For Customer Characteristics for LT20 Customer Segment		
Customer Characteristic	**Coefficient on ln(Price Ratio)**	**Coefficient on Interaction Term**
Base Case	-0.15 (-5.16)	n/a
Square feet	-0.13 (-4.28)	+0.00 (+0.33)
Proportion air conditioned	-0.07 (-0.84)	-0.07 (-0.79)
Owner occupied	-0.13 (-4.16)	-0.00 (-0.00)
Energy management system	-0.10 (-2.84)	-0.07 (-1.46)
# of workers	-0.17 (-4.81)	+0.00 (+1.87)
Standalone structure	-0.15 (-4.54)	+0.06 (+1.04)
High energy use	-0.27 (-6.25)	+0.19 (+3.67)
Satisfaction with utility	-0.08 (-0.66)	-0.02 (-0.49)

6.3 VARIATION IN PRICE RESPONSE WITH WEATHER

Determining whether customers respond to price signals differently on hot and cold days during the summer is important from a policy perspective. It is more important to get accurate estimates of price responsiveness on hot high system-load days than on average system-load days because the benefits of price response are greater on these days when the system is short on capacity and generation costs are higher.

The impact of weather was examined for the LT20 customer segment using the CES specification with an interaction term between the price term and the weather variable (e.g., the difference in cooling degree hours per hour during the peak period and cooling degree hours per hour during the off-peak period). The model was estimated using daily data rather than the 3-observation database that was used for the estimates reported above. The weather term was not significant using the 3-observation model we believe because there is insufficient longitudinal variation in weather across the 3-observation database. Using the daily data, the coefficient on the weather/price interaction term is highly significant, with a value equal -.00619 and a t-statistic equal to –3.94.[84] Inserting the value of the weather term into the demand model on the highest 20 percent of load days results in an elasticity of substitution equal to –0.13 while the value on the lowest 20 percent of system load days equals –0.09. This compares with a value of –0.13

[84] These t-statistics may be biased upward due to any autocorrelation that is present in such data.

based on a model specification with no interaction term estimated on daily data. In other words, the elasticity of substitution based on data pooled across all weather conditions is essentially the same as the elasticity of substitution on the highest 20 percent of load days. The elasticity of substitution on the lowest 20 percent of system load days is roughly a third less than on the highest system-load days.

6.4 IMPACT ANALYSIS

Table 6-4 contains percentage and absolute impact estimates for the LT20 customer segment for the average CPP-V rates tested in the SPP. The peak period estimates represent the average response over a combination of two-hour and five-hour dispatch periods. The non-CPP day impact values represent the average response for the entire six-hour peak period.

The average reduction in peak-period energy use per hour on CPP days for the combination of two-hour and five-hour dispatch periods deployed during the summer of 2003 is 25.6 percent, or 1.41 kWh/hour. The response on non-CPP days is quite small, at –3.7 percent, or –0.22 kWh/hour. Off-peak energy use on both CPP and non-CPP days increases relative to energy use under the standard rate, with the increase being higher on the non-CPP days.

Table 6-4
Impact Estimates for the LT20 Customer Segment

Unit of Measure	Rate Period	CES	
		CPP Days[85]	Non-CPP Days
Percentage Change	Peak	-25.58	-3.66
	Off-Peak	+0.86	+4.73
Change in kWh/hour	Peak	-1.41	-0.22
	Off-Peak	+0.02	+0.11

[85] These estimates represent the average response for the combination of two-hour and five-hour dispatch periods deployed in the SPP during the summer of 2003. The same percentage or absolute response may not be achieved over the entire six-hour time period on CPP days.